

Online Appendix for
“Gendered Perceptions and the Costs of Political
Toxicity: Experimental Evidence from Politicians and
Citizens in Four Democracies”

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A Experimental protocol

A.1 Technical setup

Our experimental setup relies on the development of a visual template of a social media (Twitter) post by a politician and a toxic reply by an ordinary user. To develop these templates, we designed these posts to visually match the style of replies to actual Twitter posts. Two differences from the exact replication of a Twitter post are worth noting. First, the images of the politician and user were made slightly larger to make clearer who the sender and receiver of each message was. Second, to indicate the partisanship of the politician, we place labels below each politician’s name to note their partisan affiliation (in the same style as Twitter does to indicate a user’s, for example, government affiliation).

We then wrote a script to populate this template and to output an image file for each permutation of the experimental conditions. This process resulted in roughly 4 million images files in total across the four countries of interest, which were stored on an Amazon Web Services (AWS) server that could be accessed publicly by survey software (e.g. Qualtrics). For each conjoint task, the survey software randomly selected the levels of each experimental attribute for an image that would be shown to a user. Within the survey software, a filename based on those levels was then pasted together based on the randomly selected levels (e.g. `US/Party01Po112Po1Text13User03UserText09Gendered01.jpg`) that would correspond to the relevant image file on the AWS server. In practice, we had no issues in randomizing and displaying these images to respondents.

A.2 Experimental conditions

In the experiments, the attributes in each image that were varied were the politician’s gender (name, photo); the ordinary user’s gender (name, photo); the politicians’ partisanship; the text of the tweet sent by the politician; the text of the toxic message sent by the ordinary

user; and whether the gender of the politician is highlighted in the toxic message.

As noted in the main article, we selected the names of politicians and users based on the most popular first and last names in each country context. We then randomized the selection of popular first and last names to create sets of 9 full names for women politicians and 9 full names for men politicians in each country. We then repeated this process to create sets of 9 full names for women ordinary users and 9 full names for men ordinary users. These names, for each country, are shown in [Table A1](#) and [Table A2](#).

To indicate the partisanship of politicians, we chose a well-known party to represent a political bloc/coalition in each country. In the United States, the parties represented are the Democratic Party and Republican Party; in Flanders (Belgium), Vooruit, CD&V, and N-VA; in Chile, Renovación Nacional, Partido Socialista de Chile, and Revolución Democrática; and in Denmark, Socialdemokratiet, Venstre, Socialistisk Folkeparti, and Nye Borgerlige.

We vary the text of social media posts by politicians by developing 20 messages that concern valence issues. We use valence issues rather than positional ones for two reasons. First, because positional issues often take on a much different character across country contexts, using valence issues permits us to use the same experimental conditions across each of the four countries. Second, although less importantly, in practice the development of generic toxic responses to posts about valence issues result in less awkward-sounding exchanges than those to politicians' posts about positional issues. In total, five major themes were chosen for the posts concerning valence issues: those concerning the economy, healthcare, education, crime, and national security. Descriptive survey data from the four country contexts (Gallup (US); the Eurobarometer (DK, BE); and Estudio Nacional de Opinión Pública Encuesta CEP (CL)), show that economic issues are the most important issues at the time of survey fielding. In the US, these economic issues are the high cost of living/inflation as well as broader economic issues; in Belgium and Denmark, rising prices, with a considerable portion highlighting the overall economic situation; and in Chile, the economic issues are pensions and salaries. The remaining issues used in the experiment (education, healthcare,

Table A1: Names of *politicians* used in the visual conjoint design

UNITED STATES		FLANDERS (BELGIUM)	
Woman politicians	Man politicians	Woman politicians	Man politicians
Mary Smith	James Thomas	Rita Wouters	Patrick De Smedt
Patricia Johnson	Robert Taylor	Sarah Aerts	Luc Vermeulen
Jennifer Williams	John Moore	Julie Segers	Jan Verhoeven
Linda Brown	Michael Jackson	Laura De Smet	David Smets
Elizabeth Jones	William Martin	Ann Hendrickx	Thomas De Backer
Barbara Miller	David Lee	Carine Lemmens	Paul Devos
Susan Davis	Richard Thompson	Caroline De Cock	Johan Janssens
Jessica Wilson	Joseph White	Marleen Michiels	Peter De Clercq
Sarah Anderson	Thomas Harris	Ingrid Verstraete	Dirk Coppens

CHILE		DENMARK	
Woman politicians	Man politicians	Woman politicians	Man politicians
Sofía Fernandez	Agustín Ramirez	Charlotte Lund	Henrik Iversen
Emilia Contreras	Benjamín Alvarez	Kirsten Kristiansen	Christian Thomsen
Isidora Torres	Vicente Hernandez	Inge Jensen	Anders Eriksen
Florencia Vargas	Martín Valenzuela	Bente Sørensen	Niels Jakobsen
Maite Sepulveda	Matías Sanchez	Lone Laursen	Jørgen Hansen
Fernanda Araya	Mateo Cortes	Else Rasmussen	Morten Svendsen
Martina Reyes	Joaquín Tapia	Mette Olesen	Erik Jacobsen
Josefa Castillo	Tomás Gomez	Inger Møller	Michael Johansen
Amanda Silva	Máximo Herrera	Helle Mortensen	Jesper Schmidt

Table A2: Names of *ordinary users* used in the visual conjoint design

UNITED STATES		FLANDERS (BELGIUM)	
Woman users	Man users	Woman users	Man users
Karen Clark	Charles Hill	Linda Mertens	Tom De Vos
Nancy Lewis	Chris Flores	Hilde Janssen	Bart Desmet
Linda Robinson	Daniel Green	Els Pauwels	Guy De Meyer
Betty Walker	Matthew Adams	Myriam Stevens	Vincent Hermans
Margaret Young	Anthony Nelson	Sofie Smet	Geert Jacobs
Sandra Allen	Mark Baker	Louise Martens	Yves Van de Velde
Ashley King	Don Hall	Annick Peeters	Steven Goossens
Kimberly Wright	Steven Campbell	Eva Wauters	Wim Claeys
Emily Scott	Paul Mitchell	Inge Claes	Erik Van den Broeck

CHILE		DENMARK	
Woman users	Man users	Woman users	Man users
Agustina Vasquez	Alonso Espinoza	Pia Petersen	Thomas Christiansen
Catalina Perez	Maximiliano Lopez	Maria Frederiksen	Ole Andersen
Antonia Flores	Cristóbal Fuentes	Anne Kristensen	Peter Andreasen
Isabella Muñoz	José Rodriguez	Anna Knudsen	Martin Clausen
María Morales	Lucas Rojas	Hanne Mikkelsen	Jan Pedersen
Trinidad Gutierrez	Sebastián Martinez	Marianne Poulsen	Søren Jeppesen
Valentina Diaz	Felipe Gonzalez	Karen Nielsen	Lars Østergaard
Javiera Castro	Diego Carrasco	Susanne Olsen	Jens Simonsen
Julieta Soto	Nicolás Nuñez	Lene Christensen	Hans Larsen

crime, and security) have lower salience across the countries. Education and healthcare rank in the middle in terms of importance, and crime-related concerns are largest in Chile. Although security issues are listed as most important issues, these are more difficult to compare cross-nationally because of variation in the categories from the data sources.

To develop texts for these themes, we qualitatively examined recent Twitter posts from politicians, and wrote posts that mimic the tone and style of existing messages. Past research shows some differences in how women and men politicians use social media: women politicians use it more frequently than men; interact more with other users on social media; and are more likely to focus on topics traditionally associated with women (e.g. health care and education) (Meeks, 2016; Evans and Clark, 2016; Wagner, Gainous and Holman, 2017; Beltran et al., 2021; Butler, Kousser and Oklobdzija, 2023). The differences in the topics discussed on social media by women and men politicians, however, have been shown recently to be relatively minor (Russell, 2021), and the ideological content of tweets is similar (Butler, Kousser and Oklobdzija, 2023). In our qualitative use of Tweets from politicians as examples of valence issue tweets, we did not note any meaningful differences in gendered tone of language between women and men.

The social media posts that we developed for politicians were first written in English and then, to ensure their suitability for all contexts, were examined by Danish-speaking, (Chilean) Spanish-speaking, and Flemish-speaking political scientists who are familiar with each of the country contexts. The English texts, shown in Table A3, were then translated by political scientists whose first languages are (Chilean) Spanish, Danish, and (Flemish) Dutch. Because the salience of the topics of the texts might differ across country contexts, we test in Appendix M whether the effect of a woman or man politician on understandings of toxicity depend on the topic of the text of a politician’s post. We find no evidence that what politicians post, in general, moderates the effect of a politician’s gender, either among the politician or citizen respondents.

Table A3: Text of social media posts by politicians

1	Economy	We need to remove barriers that limit opportunities for those seeking jobs in government. The bill we’re introducing today will ensure that skills and experience count as much as formal education.
2	Economy	I entered politics to get things done for everyday citizens and make sure that the economy works for everyone. The bill we’re introducing today will create jobs, and reinvent our economy.
3	Economy	Even as our economy recovers, food prices are making it hard for families in this country to stay afloat. Today I am calling on us all to find concrete actions to address this situation & lower prices.
4	Economy	I continue to push for new laws to ensure that small businesses in our communities have access to the resources they need. Supporting small businesses will always be a top priority.
5	Health	Diabetes and heart disease are leading causes of death and disability. To protect the health of all of us, we introduce a series of new initiatives today to help fight these chronic diseases.
6	Health	COVID-19 restrictions have had terrible effects on our children—lost learning, isolation, & mental health problems. All of us must come together to find solutions to support our next generation.
7	Health	It is unacceptable that there are shortages for healthcare workers for personal protective equipment (PPE). I am calling on the government to help ramp up production of PPE for these workers.
8	Health	I met with healthcare professionals and community members this morning to discuss how we can improve our healthcare system. It’s time for commonsense solutions that benefit all of us.
9	Education	Every person in this country deserves quality education and a safe environment to learn in. I continue to fight for reforms that will improve education, and today we will introduce a bill that will do just that.
10	Education	I constantly hear from workers, business owners & students about increasing enrollment in technical skills programs. That’s why I’m examining how to better support these programs.
11	Education	If a budget reflects our values, then cuts to education tell you that a politician doesn’t value education in this country. I will always stand up for our kids, parents, and the teachers who support them.
12	Education	We must focus on safely reopening schools. This is in line with the scientific guidance, which supports reopening and highlights the consequences of children not receiving in-person education.
13	Crime	Crime and violence are still part of the reality for many in poorer communities. They are not invisible. Together we can raise awareness and combat this situation with policies that empower our communities.
14	Crime	Voters expect that government works to keep our communities safe. The lack of concern about crime is troubling. I will continue to promote commonsense solutions to protect all of us.

15	Crime	It is depraved that criminals are exploiting our current public health and economic crisis. Yet these scams are proliferating. I speak with media outlets today about how citizens can protect themselves.
16	Crime	The increased focus on violence intervention programs to prevent gang violence is critical. I remain committed to working with government & community leaders to ensure our families and citizens remain safe.
17	National security	Cyber attacks give our enemies opportunities to steal intellectual property & harm infrastructure. Today, I asked our defense professionals to propose concrete solutions to guard against these intrusions.
18	National security	Protecting our national security means strengthening our cybersecurity defenses. I meet with defense professionals today to identify solutions to this threat to our country and communities.
19	National security	I am pleased that many of us, no matter our party, are pushing to strengthen ties with our international allies. We must all work together toward peace and prosperity.
20	National security	Building a coalition of our allies to stand up and defend democracy should remain a foreign policy priority in this country. It is in our national interest to support those who support us.

To develop a set of toxic replies to politicians that are made by ordinary users, we used the Twitter API to collect tweets sent by users to politicians, and used Google’s Perspective API (Wulczyn, Thain and Dixon, 2017; Lees et al., 2022) to rate and rank them by their level of toxicity. We used these tweets as templates to develop 18 toxic posts that have a tone that can be considered as “everyday” toxicity: toxic responses that politicians might ordinarily expect in response to a post on social media. These posts include those that are roughly in the upper 20th percentile of those ranked by the Perspective API. Because we wanted to also vary whether a toxic post notes the gender of the politician, we develop posts such that the gender of the politician can be stated explicitly in the post (“woman”, “man”, “his”, “her”). The toxic messages from ordinary users that are used in the experiment are presented in Table A4. As with the texts from politicians, toxic comments from ordinary users were first written in English, and then translated by political scientists whose first languages are (Chilean) Spanish, (Flemish) Dutch, and Danish.

Table A4: Text of toxic responses to politicians by ordinary users

-
- 1 What a joke this is. Give me a break. This [politician/woman/man] is a total moron. How can anyone even think it's worth listening to [people/women/men] like this?
 - 2 omg, not this idiot[/ic woman/ic man] again. No one in their right mind believes anything [this politician says/she says/he says] anyway. Give me a break.
 - 3 The simple truth is that 99% of what [this politician says/this woman says/this man says] is utterly stupid. Imagine being that dumb. Can't wait for [this person/her/him] to be voted out!
 - 4 Sorry folks, but [this politician/this woman/this man] is awful. This jackass is trying to cover up for being a failure. The country deserves much better than [people/women/men] like this.
 - 5 Please stop talking and do your job. When is this country going to realize that [people/women/men] like this are lying. Take it from me, [this politician/this woman/this man] is a clown.
 - 6 Every day [this politician/this woman/this man] proves [/ herself/ himself] to be the dumbest [person/woman/man] in the country. How can anyone believe this is sincere? Total idiocy.
 - 7 Oh god, you are the total [champion/queen/king] of misdirection. If you think we forget what [politicians/women/men] like you did to this country, you are pretty stupid.
 - 8 Nothing but a liar. [Politicians/Women/Men] like [this/her/him] don't care about anyone but themselves. Total embarrassment to the country. Go home and don't show your face again.
 - 9 I sure hope that only a small number of fools believe this [politician's/woman's/man's] insincere & idiotic tweets. If more [people/women/men] like [this/her/him] are voted into office, we're in serious trouble.
 - 10 Cut the crap. All of this is pure spin. I can't imagine a [politician/woman/man] who is more two-faced than this. This [person/woman/man] just thinks we're all stupid. Absolute slimeball.
 - 11 Corrupt, incompetent, and [/she/he] thinks we're too stupid to see it. If only this [politician/woman/man] would do something for someone else for once. [Total/She's a total/He's a total] sellout.
 - 12 Everyone sees through this. I haven't seen a [politician/woman/man] lie so much and do so little. [An/She's an/He's an] utter embarrassment to the country. Vote [this person/her/him] out before it's too late!
 - 13 This is the best this [politician's/woman's/man's] got for deflecting away from all the scandals? Everyone knows how incompetent [this person/she/he] is. Good luck in the next election moron!
 - 14 Doesn't everyone know how corrupt this [person/woman/man] is? Stop believing this idiot's garbage! A [politician/woman/man] with no principles who just wants \$\$\$ from corporate lobbyists!
 - 15 Hey idiot, you're not fooling anyone with this. If [people/women/men] like this had more sense, we wouldn't need to read such insincere self-serving garbage. Vote [em/the woman/the man] out!

- 16 The staff must have written this tweet, because I just saw this dumbass [politician/woman/man] on TV not able to put two words together. [This person/The woman/The man] isn't fit to be a politician.
-

B Pre-registration

The pre-registration for the hypotheses and experimental design can be found here: https://osf.io/q3p2a/?view_only=619d8054ff7b4eb58e94393c396ddab2

Article hypothesis number	Pre-registration hypothesis number
H1	H1
H2	H5A/H5B
H3	H6
H4	H2
H5	H3
H6	H4
H7	H10
H8	H5C/H5D

Table B5: Comparison between the citizen sample and the population in the United States. Hypotheses H7, H8, H9, and H11 in the pre-registration are not formally introduced in the theoretical section of the article, but are referenced in the Results section and tested in [Appendix I](#).

In writing the main article, the clarity and framing of the article benefited from changing the order in which the hypotheses from the pre-registration are introduced. The numbering of the hypotheses in the article are sequential to increase readability, but this means that the hypothesis numbers in the article do not align with the hypothesis numbers in the pre-registration. For reference, [Table B5](#) presents each hypothesis number from the main article and the corresponding hypothesis number in the pre-registration. All hypotheses in the pre-registration are empirically tested in the paper.

C Survey details and sample characteristics

C.1 Citizen sample

The surveys were sent to representative samples of respondents in the United States, Belgium (Flanders), Chile, and Denmark by the survey firm Dynata (formerly SSI International) in March, 2022. The resulting sample sizes for each citizen survey were 1,486 (United States), 1,230 (Belgium), 1,331 (Chile), and 1,329 (Denmark). Sample characteristics (and analogous population values) for each of these countries are presented in [Table C6](#), [Table C7](#), [Table C8](#), and [Table C9](#). The education variable in each table refers to a measure of education (“Low”, “Middle”, and “High”) as defined by the survey firm for comparison to known values in each country’s population. These categories roughly break down as (a) below high school, (b) high-school/non-university degree, (c) university degree and above (see table notes for details per country). The party ID variable is measured by a question asking the national-level political party to which a respondent feels closest. To help ensure that respondents paid sufficient attention to the conjoint tasks, we included an attention check question in the citizen surveys. The vast majority of respondents passed this check. Those who did not, are excluded from the analysis.

C.2 Politician sample

Surveys of politicians were conducted by the authors in Belgium, Chile, and Denmark by creating lists of the emails of politicians in local and national office. In the US, the survey was fielded by CivicPulse. In Belgium, Chile, and Denmark, all politicians received survey invitations. As we note further below, in the US, politicians were probabilistically sampled based on estimated response rates to increase representativeness.

Our sample of representatives in Denmark was compiled in February/March 2022 and includes all members of the Danish Parliament (the Folketing) as well as the Danish munic-

	Sample %	Population %
Gender: Men	46.4	48.5
Gender: Women	53.6	51.5
Age: 18-24	11.8	13.1
Age: 25-34	18.4	17.5
Age: 35-44	20.6	17.5
Age: 45-54	17.0	19.2
Age: 55-64	16.3	15.6
Age: 65+	15.9	17.2
Education: Low	11.0	12.6
Education: Middle	50.8	49.5
Education: High	38.2	38.0
Region: Midwest	21.1	21.7
Region: Northeast	18.1	18.3
Region: South	38.3	37.0
Region: West	22.5	23.0
Party ID: Democratic Party	34.1	–
Party ID: Republican Party	33.9	–
Party ID: Other	5.0	–
Party ID: Does not identify	27.1	–
n = 1,486		

Table C6: Comparison between the citizen sample and the population in the United States.

This table presents the sample characteristics of the US citizen sample, and associated values among the US population. Education is coded as Incomplete Secondary (high school) Education (“Low”), Secondary (high school) Education (“Middle”), Some College, University, Technical School or Further Education (“High”), Vocational or Technical Degree (“High”), Associate’s Degree (“High”), Bachelor’s Degree (“High”), Master’s Degree (“High”), Doctoral or Professional Degree (PhD, Ed.D, JD, DVM, DO, MD, DDS, or similar) (“High”). Party ID is measured by the question “Do you consider yourself close to a particular political party? If so, which party do you feel closest to?”

	Sample %	Population %
Gender: Men	43.0	49.0
Gender: Women	57.0	51.0
Age: 18-24	8.0	10.3
Age: 25-34	14.9	15.4
Age: 35-44	19.0	16.2
Age: 45-54	16.1	18.5
Age: 55-64	16.4	15.9
Age: 65+	25.6	23.6
Education: Low	25.3	29.7
Education: Middle	39.4	37.7
Education: High	35.4	32.6
Region: Antwerpen	27.5	27.9
Region: Limburg	14.5	13.5
Region: Oost-Vlaanderen	23.7	22.9
Region: Vlaams-Brabant	15.2	17.1
Region: West-Vlaanderen	19.1	18.6
Party ID: CD&V	4.5	–
Party ID: Groen	6.6	–
Party ID: N-VA	12.5	–
Party ID: Open Vld	4.6	–
Party ID: PvdA	5.9	–
Party ID: Vlaams Belang	14.3	–
Party ID: Vooruit	8.4	–
Party ID: Other	1.1	–
Party ID: Does not identify	42.1	–
n = 1,230		

Table C7: Comparison between the citizen sample and the population in Flanders (Belgium).

This table presents the sample characteristics of the Belgian (Flemish) citizen sample, and associated values among the Belgian (Flemish) population. Education is coded as Incomplete Secondary Education (“Low”), Secondary Education Completed (“Middle”), Some University or Vocational Certification (“Middle”), Vocational or Professional Certification Completed (BTS, DUT or equivalent) (“Middle”), University Education Completed (Bac+3) (“High”), Postgraduate Education Completed (Bac+5: Master, Engineering Degree or equivalent) (“High”), Doctorate, Post-doctorate or equivalent (Bac +8) (“High”). Party ID is measured by the question “Do you consider yourself close to a particular political party? If so, which party do you feel closest to?”

	Sample %	Population %
Gender: Men	42.9	49.2
Gender: Women	57.1	50.8
Age: 18-24	16.2	16.4
Age: 25-34	26.8	21.6
Age: 35-44	24.7	19.4
Age: 45-54	17.9	20.0
Age: 55-64	10.1	14.0
Age: 65+	4.3	8.6
Education: Low	18.6	22.1
Education: Middle	56.1	56.5
Education: High	25.3	21.4
Region: Aisén del General Carlos Ibáñez del Campo	0.5	0.6
Region: Antofagasta	3.1	3.3
Region: Araucanía	4.7	5.5
Region: Arica and Parinacota	1.3	1.3
Region: Atacama	1.5	1.8
Region: Bío-Bío	8.4	11.9
Region: Coquimbo	4.0	4.3
Region: Libertador General Bernardo O'Higgins	4.7	5.3
Region: Los Lagos	5.6	4.7
Region: Los Ríos	1.2	2.2
Region: Magallanes y Antártica Chilena	0.8	1.0
Region: Maule	4.9	5.8
Region: Región Metropolitana de Santiago	45.2	40.3
Region: Tarapacá	2.4	1.8
Region: Valparaíso	11.7	10.4
Party ID: Comunes	1.3	–
Party ID: Convergencia Social	1.2	–
Party ID: Evolución Política	0.5	–
Party ID: Federación Regionalista Verde Social	0.3	–
Party ID: Partido Comunista de Chile	2.4	–
Party ID: Partido de la Gente	3.9	–
Party ID: Partido Demócrata Cristiano	2.5	–
Party ID: Partido Liberal de Chile	1.2	–
Party ID: Partido por la Democracia	3.2	–
Party ID: Partido Radical de Chile	0.5	–
Party ID: Partido Republicano de Chile	4.8	–
Party ID: Partido Socialista de Chile	3.0	–
Party ID: Renovación Nacional	3.4	–
Party ID: Revolución Democrática	0.8	–
Party ID: Unión Demócrata Independiente	2.7	–
Party ID: Does not identify	68.4	–
n = 1,331		

Table C8: Comparison between the citizen sample and the population in Chile. This table presents the sample characteristics of the Chilean citizen sample, and associated values among the Chilean population. Education is coded as Incomplete Secondary Education (“Low”), Secondary Education Completed (“Middle”), Some University or Vocational Certification (“Middle”), Vocational Certification or University Completed (“High”), Postgraduate Education Completed (“High”), Doctorate, Post-doctorate or equivalent Completed (“High”). Party ID is measured by the question “Do you consider yourself close to a particular political party? If so, which party do you feel closest to?”

	Sample %	Population %
Gender: Men	44.3	49.1
Gender: Women	55.7	50.9
Age: 18-24	10.0	11.2
Age: 25-34	15.9	14.9
Age: 35-44	19.2	17.8
Age: 45-54	16.9	18.0
Age: 55-64	19.1	16.1
Age: 65+	18.9	22.0
Education: Low	16.2	17.5
Education: Middle	54.9	54.0
Education: High	28.9	28.6
Region: Hovedstaden	28.0	31.0
Region: Midtjylland	22.4	22.5
Region: Nordjylland	11.7	10.5
Region: Sjælland	15.9	14.6
Region: Syddanmark	21.9	21.4
Party ID: Alternativet (ALT)	1.0	–
Party ID: Dansk Folkeparti (DF)	5.5	–
Party ID: Det Konservative Folkeparti (KF)	7.6	–
Party ID: Enhedslisten (EL)	6.5	–
Party ID: Frie Grønne (FG)	1.4	–
Party ID: Kristendemokraterne (KD)	0.8	–
Party ID: Liberal Alliance (LA)	3.1	–
Party ID: Nye Borgerlige (NB)	7.8	–
Party ID: Radikale Venstre (RV)	3.6	–
Party ID: Socialdemokratiet (S)	23.6	–
Party ID: Socialistisk Folkeparti (SF)	6.4	–
Party ID: Venstre (V)	8.2	–
Party ID: Other	1.7	–
Party ID: Does not identify	23.0	–
<hr/>		
n = 1,329		

Table C9: Comparison between the citizen sample and the population in Denmark. This table presents the sample characteristics of the Danish citizen sample, and associated values among the Danish population. Education is coded as Incomplete Secondary Education (“Low”), Secondary Education Completed (Baccalauréat or equivalent) (“Middle”), Some University or Vocational Certification (“Middle”), Vocational or Professional Certification Completed (BTS, DUT or equivalent) (“Middle”), University Education Completed (Bac+3) (“High”), Postgraduate Education Completed (Bac+5: Master, Engineering Degree or equivalent) (“High”), Doctorate, Post-doctorate or equivalent (Bac +8) (“High”). Party ID is measured by the question “Do you consider yourself close to a particular political party? If so, which party do you feel closest to?”

ipality and regional councils. We relied on official websites and information from the Danish associations of Municipalities and Regions to gather the list of representatives and their contact details. Responses were received from 1,049 politicians (a response rate of 37%). A comparison of politician respondent characteristics is provided in [Table C11](#).

The target population in Chile was elected representatives at all government levels. The list was compiled from December 2021 to February 2022. It included representatives from local governments (majors and councils), regional governments (governors and regional council), the Constitutional Convention and the national Congress. As elections were held at the time the survey started for the latter, both outgoing and incoming congresspeople were included in the sample. As no previous systematization of contact details of Chilean representatives existed, research assistants compiled the contact information from a variety of websites including the official websites of municipalities and regional governments. A total of 2,700 representatives were contacted, of which 1,700 were contacted directly via personal emails. The remaining representatives were contacted through the secretaries and staff of their elected bodies. Responses were received from 384 politicians (a response rate of 14%). A comparison of politician respondent characteristics is provided in [Table C13](#).

The Belgian sample of politicians was collected from Dutch-speaking politicians elected at the local level (municipality, city, or provincial level) in Belgium (Flanders and Brussels). A total of 6,659 politicians were invited to the survey, of which 906 responded (a response rate of 14%). A comparison of politician respondent characteristics is provided in [Table C12](#).

Finally, the US sample of politician respondents was collected by CivicPulse, and consisted of elected policymakers that were drawn from U.S. local governments (i.e., township, municipality, and county governments) with a population over 1,000 residents. Elected policymakers include top elected officials and governing board members. 11,126 elected policymakers were invited by CivicPulse to the survey, of which 478 responded (a response rate of 4.3%). A comparison of politician respondent characteristics is provided in [Table C10](#). CivicPulse samples politicians probabilistically based on known estimates of response rates

	Sample %	Population %
Gender: Men	65	73
Gender: Women	35	26
Proportion urban (county politicians)	54	40
Proportion college-educated (county politicians)	24	19
Population size (county politicians)	59,600	25,800
Democratic vote share (county politicians)	41	30
Proportion urban (municipal politicians)	99	97
Proportion college-educated (municipal politicians)	32	21
Population size (township politicians)	6,700	4,000
Democratic vote share (municipal politicians)	47	39
Proportion urban (township politicians)	12	1
Proportion college-educated (township politicians)	32	22
Population size (township politicians)	4,200	2,600
Democratic vote share (township politicians)	50	39
n = 478		

Table C10: Comparison between the politician sample and the politician population in the United States. Population and sample data provided by the survey firm CivicPulse.

among sub-groups in their data to achieve representativeness. We note, therefore, that unlike in Belgium, Chile, and Denmark, in which all politicians received survey invitations, the sampling strategy in the US was different.

Similar to other elite surveys, our response rates vary cross-nationally. Differences in the response rates align with those in other country samples, as identified by a recent meta-study of elite surveys in legislative research, which parallel those observed in our study (Bailer, 2014). In the United States, the survey was conducted by CivicPulse, which fields its surveys to politicians to optimize representativeness, even if the resulting response rate (4%) is lower than in other countries.

	Sample %	Population %
Gender: Men	57.4	63.0
Gender: Women	42.6	37.0
Party ID: Social-Democratic	32.5	28.4
Party ID: Liberal	25.2	27.6
Party ID: Christian-Democratic/Conservative	16.8	15.1
Party ID: Radical Left	16.0	11.0
Party ID: Radical Right	5.1	5.9
Party ID: Green	0.5	0.4
Party ID: Special Interest	0.1	–
Party ID: Independent from national parties	3.7	4.1
Party ID: Not linked to any parties	0.1	0.4

n = 1,053

Table C11: Comparison between the politician sample and the politician population in Denmark. Population values for the gender and party ID of politicians were coded manually. Given the large number of local parties, the party ID of politicians were grouped into blocs.

	Sample %	Population %
Gender: Men	67.2	65.9
Gender: Women	32.8	34.1
Party ID: CD&V	26.1	22.0
Party ID: N-VA	24.3	20.0
Party ID: Open Vld	10.2	11.0
Party ID: Vooruit	10.6	7.0
Party ID: Groen	12.4	6.0
Party ID: Vlaams Belang	3.2	6.0
Party ID: PvdA	1.3	0.0
Party ID: Other	12.0	28.0

n = 906

Table C12: Comparison between the politician sample and the politician population in Flanders (Belgium). Population values for the gender and national party ID of local politicians are taken from the Agentschap Binnenlands Bestuur report on local politicians. Party ID is measured by the question “Do you consider yourself close to a particular political party? If so, which party do you feel closest to?”

	Sample %	Population %
Gender: Men	53.8	68.1
Gender: Women	46.2	31.9
Party ID: Nueva Mayoria	38.5	31.9
Party ID: IND	33.3	36.6
Party ID: Chile Vamos	15.2	23.7
Party ID: Frente Amplio	9.2	6.4
Party ID: Other	3.8	1.3
n = 384		

Table C13: Comparison between the politician sample and the politician population in Chile. Population values for the gender and party ID of politicians were coded manually. Given the large number of local parties, the party ID of politicians were grouped into blocs.

D Descriptive questions concerning beliefs about political toxicity

In the survey, we asked both politician and citizen respondents about the extent that toxic behavior toward politicians on social media is a problem. Respondents were asked how concerned they are about toxic comments sent to politicians, and whether they believe that the government should do more to restrict this kind of discourse.

We present results for these questions in [Figure D1](#), both in aggregate and broken down by respondents' gender. Panel A shows that politicians express higher levels of concern (59%) than citizens (31%) about toxic messages sent to politicians on social media, and women politicians express more concern (64%) than their counterparts who are men (55%).

Panel B shows that a majority of respondents believe that the government should do more to limit toxic discourse on social media, with citizens expressing slightly more agreement (63%) than politicians (58%). Women politicians and women citizens express higher levels of support (65% & 68% respectively) for more government action compared to men politicians and citizens (53% & 56% respectively). Finally, women politicians who indicate having personally experienced toxic behavior themselves (not shown) are also more likely to express higher levels of concern about toxicity toward politicians (66%) and desire for more government action (67%) than their counterparts who are men and who have also

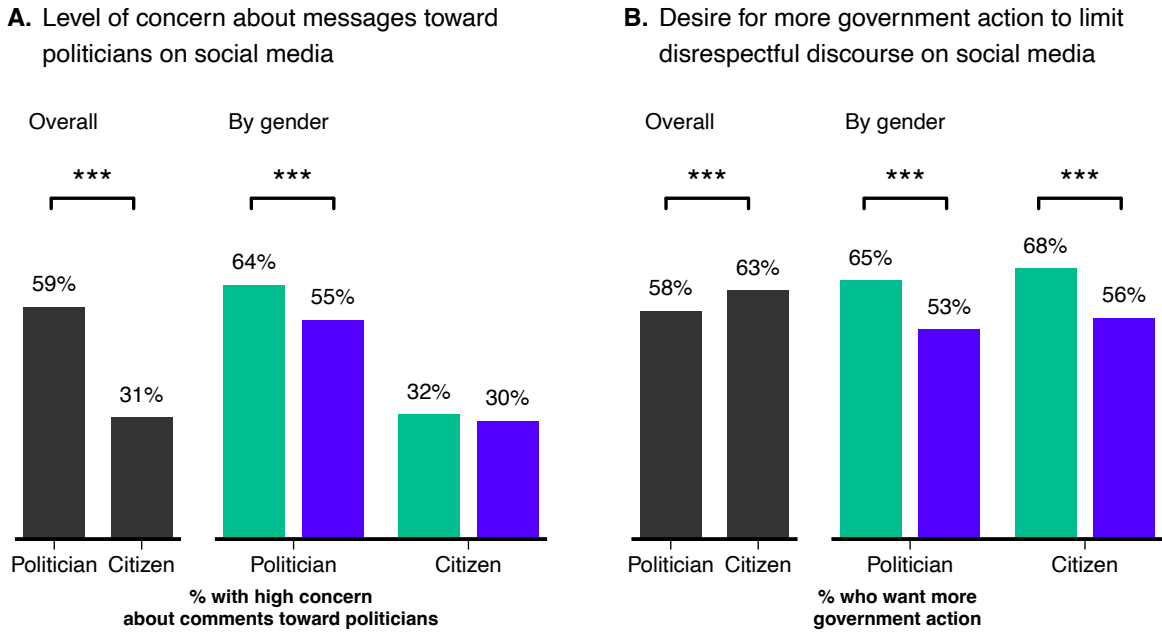


Figure D1: Differences in attitudes toward toxic comments toward politicians on social media among citizen and politician respondents. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Panel A presents the percentage of respondents who are women and men in the citizen and politician sample who answer “Moderately concerned” or “Extremely concerned” when asked how concerned they are about disrespectful comments sent to politicians on social media (compared to “Not concerned at all”, “Slightly concerned”, or “Somewhat concerned”). Panel B presents analogous results for respondents when asked the extent that they disagree or agree that stronger government action should be taken to restrict disrespectful discourse on social media. Citizen sample respondents (Panel A) = 5,346; politician sample respondents (Panel A) = 2,066; citizen sample respondents (Panel B) = 5,347; politician sample respondents (Panel B) = 2,064.

experienced such behavior (57%, 51% respectively).

In sum, women both show more concern about online toxicity toward politicians and express more support for government action to combat it compared to men.

E Results by country sample

In this section, we provide country-level estimates of results from the main article. In general, we find few systematic differences in the magnitudes of the effect of each of the variables of interest. As each of the figures presented below show, there are relatively few significant differences between countries.

E.1 Gendered text & male user interaction results by country

In [Figure E2](#) and [Figure E3](#) we present graphs analogous to Panels A and B in Figure 4 in the main article, with the pooled estimate placed alongside estimates for each the attributes estimated separately for each of the four countries in the study. Overall, we do not observe any major differences in estimates across countries, with relatively few estimates that are significantly different from each other for each attribute.

E.2 Effects of a politician’s gender by sub-group

In [Figure E4](#) and [Figure E5](#), we present analogous results to Figure 5 in the main article, broken down by country, which demonstrate the effect of the gender of the politician among subgroups within each country sample. In almost all cases, we find no significant differences in the magnitude of the effect of a politician being a woman across any sub-group in each of the country cases.

E.3 Mechanisms

In [Figure E6](#) we present estimates analogous to Figure 6 in the main article broken down by country, for the effect of a politician in a conversation being a woman on perceptions of the motivation of the perpetrator. As the figure shows, there are few differences in the magnitude of this effect across countries for each of the mechanisms.

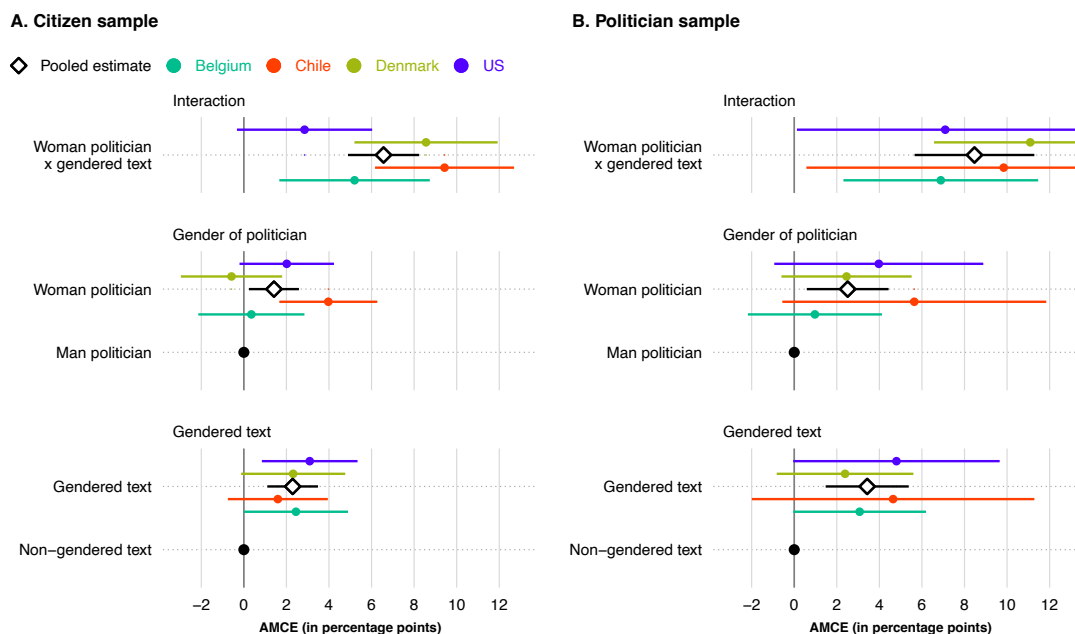


Figure E2: Effect of the politician’s gender conditional on whether the text is gendered (by country) This figure presents point estimates and 95% confidence intervals, by country sample, for each attribute of interest, and interactions between the politician’s gender and whether the text is gendered. The “pooled estimate” is the estimate of each effect for each level for the pooled sample of all respondents in the citizen sample (Panel A) and politician sample (Panel B). Robust standard errors are clustered at the level of the respondent.

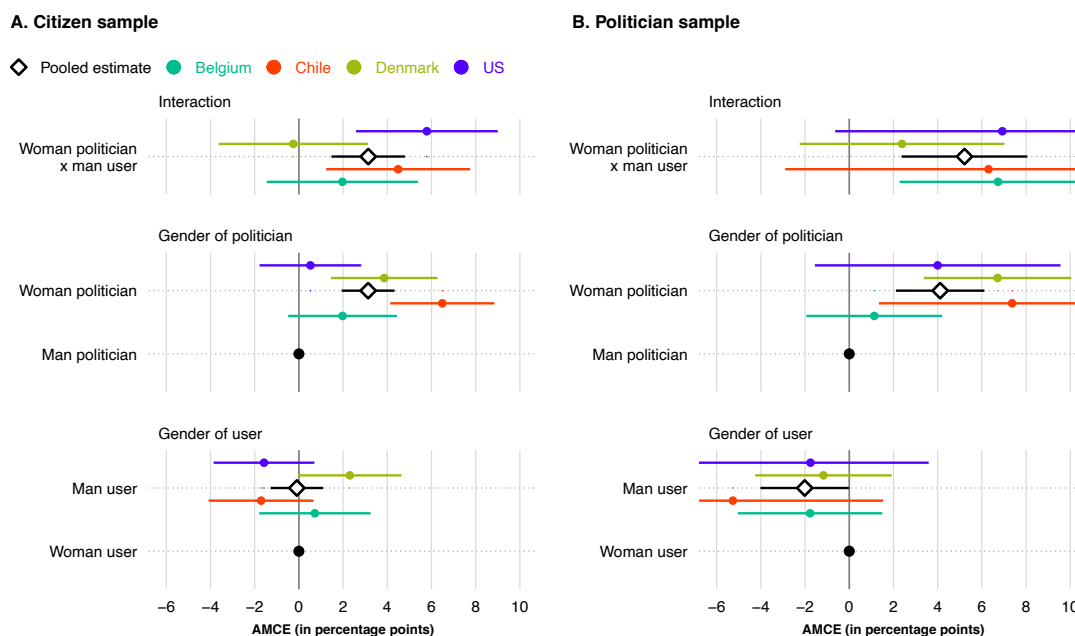


Figure E3: Effect of the politician’s gender conditional on the user’s gender (by country) This figure presents point estimates and 95% confidence intervals, by country sample, for each attribute of interest, and interactions between the user’s gender and the gender of the politician. The “pooled estimate” is the estimate of each effect for each level for the pooled sample of all respondents in the citizen sample (Panel A) and politician sample (Panel B). Robust standard errors are clustered at the level of the respondent.

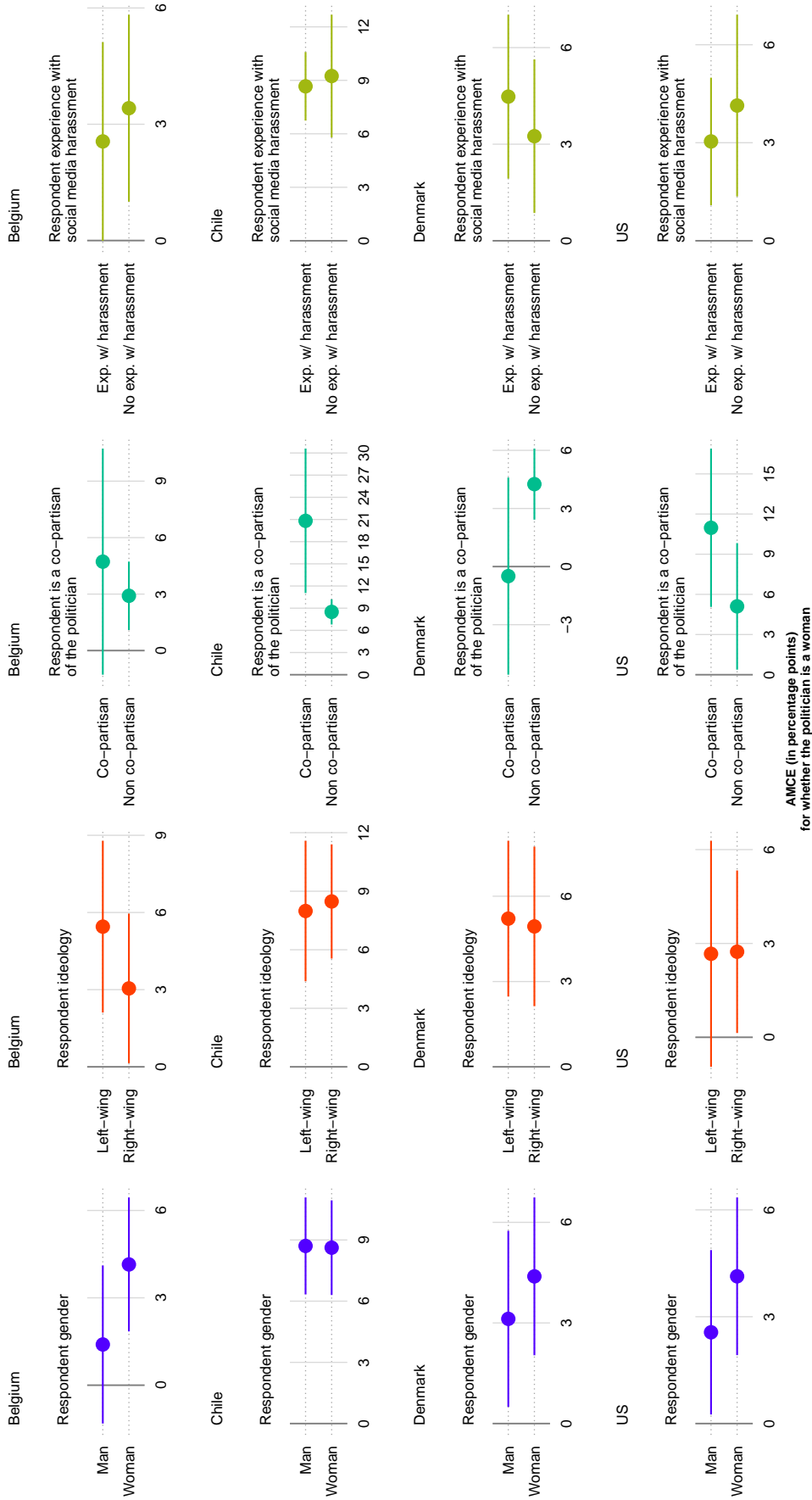


Figure E4: Effects of politician’s gender on perceptions of toxic behavior by citizen respondent sub-groups (by country). This figure presents point estimates and 95% confidence intervals of the effect of the gender of a politician on perceptions of toxic behavior for respondent subgroup characteristics among citizen respondents, broken down by country sample. Robust standard errors are clustered at the level of the respondent.

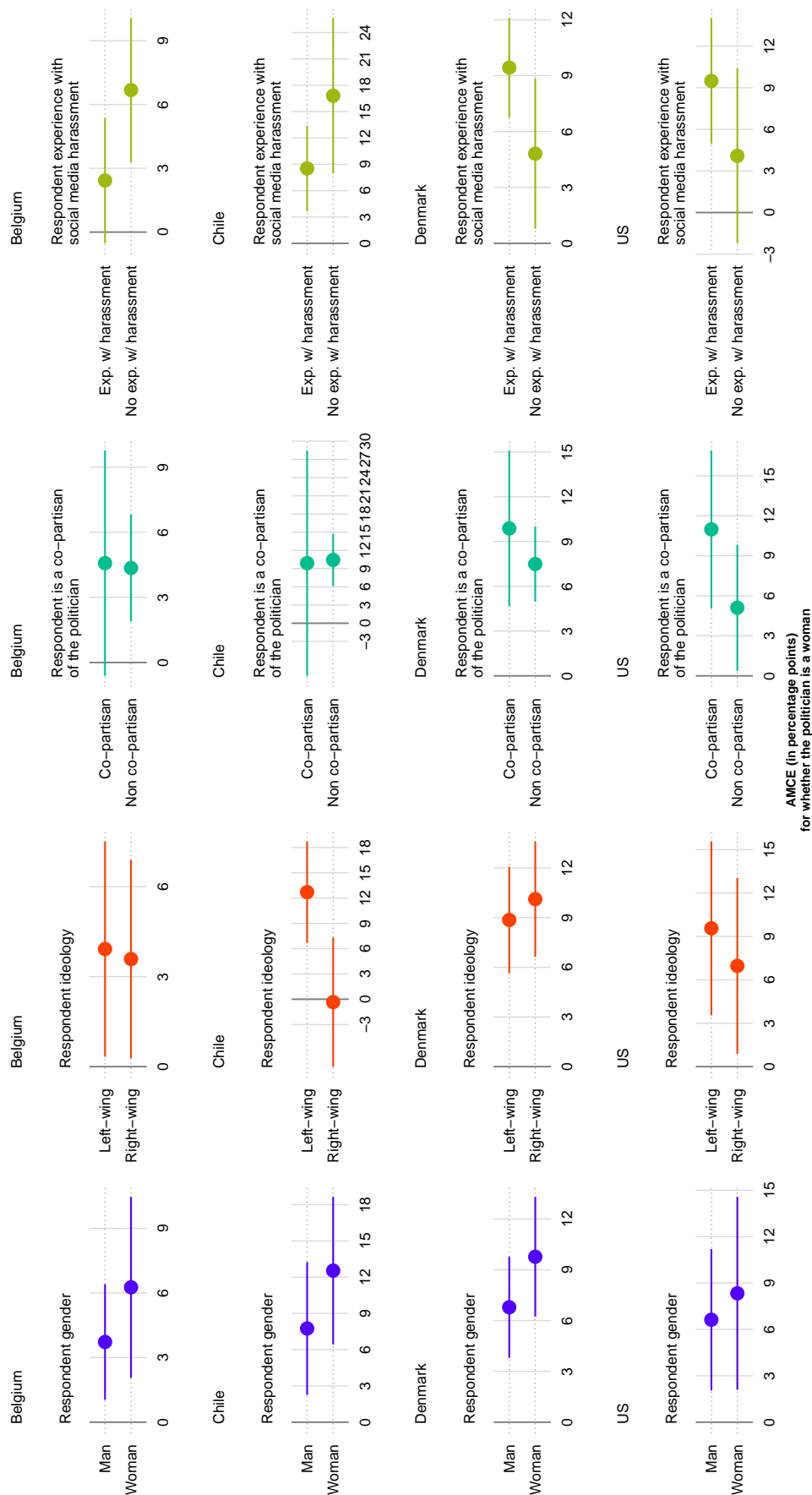


Figure E5: Effects of politician's gender on perceptions of toxic behavior by politician respondent sub-groups (by country). This figure presents point estimates and 95% confidence intervals of the effect of the gender of a politician on perceptions of toxic behavior for respondent sub-group characteristics among politician respondents, broken down by country sample. Robust standard errors are clustered at the level of the respondent.

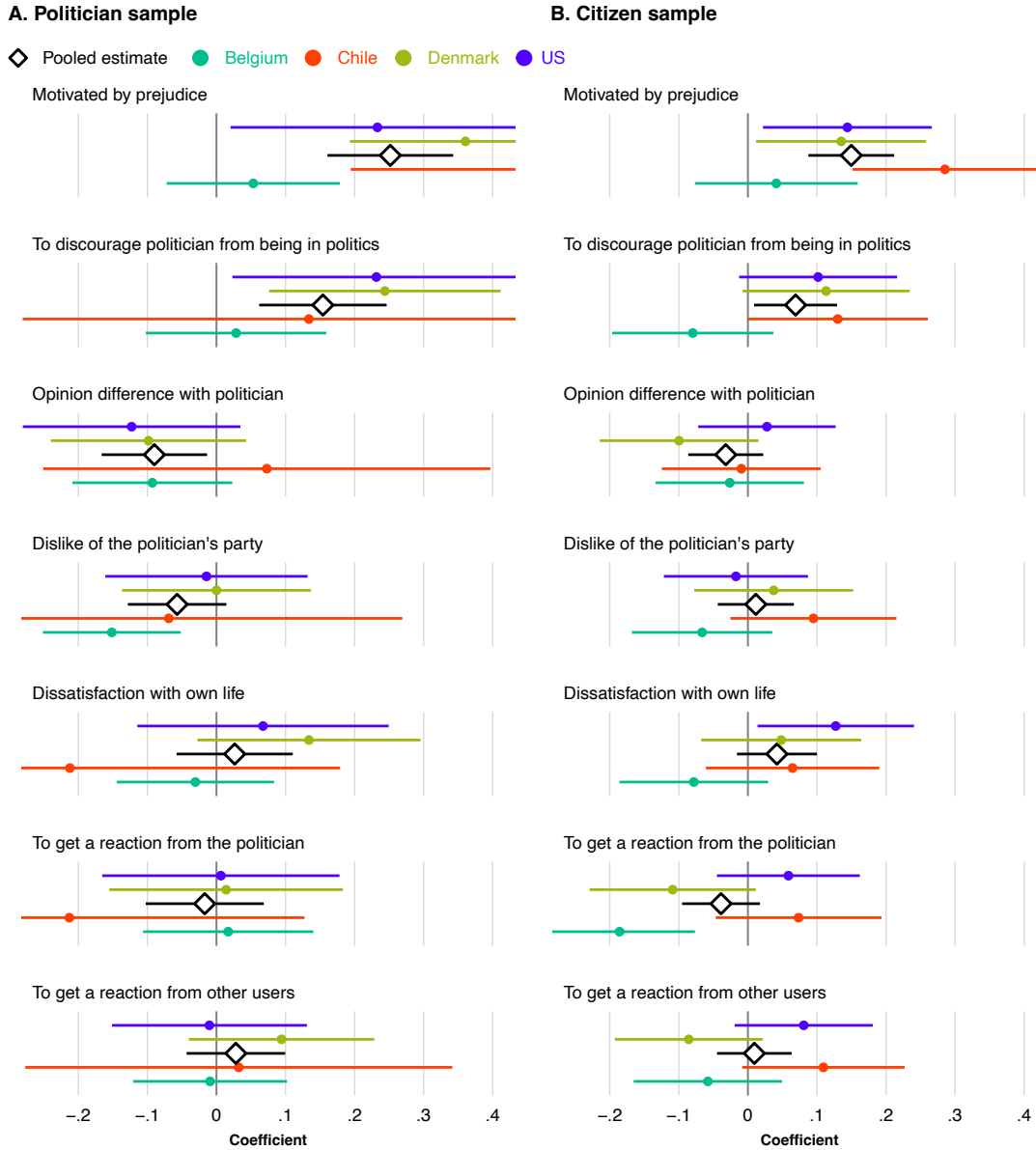


Figure E6: Effects of a politician's gender on perceptions of motivations behind toxic behavior (by country). This figure presents point estimates and 95% confidence intervals for the effect of a politician's gender on seven separate outcomes (by country). Each point represents the effect of politician gender on each mechanism outcome, as estimated from seven separate models. The "pooled estimate" is the estimate of each effect for each level for the pooled sample of all respondents in the politician sample (Panel A) and citizen sample (Panel B). Robust standard errors are clustered at the level of the respondent, with country fixed effects.

F Mechanisms conditional on gendered text and user gender

In Figure 7 in the main article, we present results for the effect of the gender of the politician conditional on whether the text of the toxic message is gendered and whether the user sending a toxic message is a man. We present analogous results for the outcome of whether respondents perceive the user of desiring to push the politician out of office in Figure F7. As we can see in both Panels A and B, we find no strong evidence that the magnitude of the effect of the politician being a woman on perceptions of a user wanting to push the politician out of politics is modified by whether the text is gendered or the user is a man.

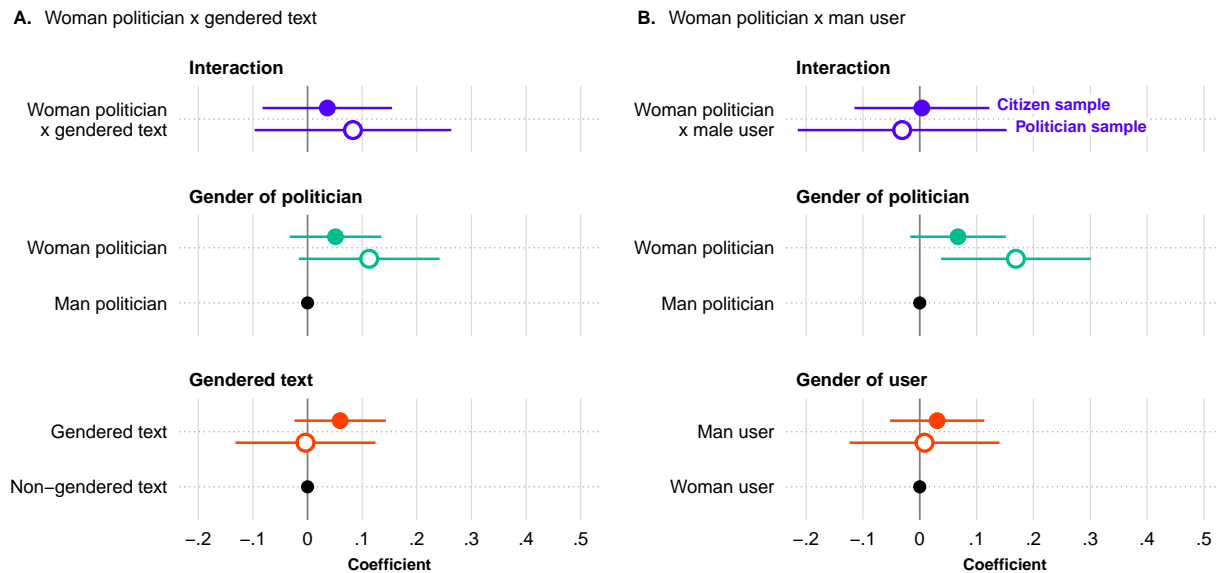


Figure F7: Effects of politician’s gender on perceptions of whether a user desires to push the politician out of office conditional on whether the message is gendered and whether the user is a woman or man. This figure presents point estimates and 95% confidence intervals for each attribute of interest. Robust standard errors are clustered at the level of the respondent, with country fixed effects.

G Mechanisms as predictors of perceptions of toxicity

In the “Mechanisms” sub-section of the main article’s Results section, we note that mechanisms concerning prejudice, a desire to discourage a politician from being in office, and

opinion differences with the politicians, are affected by whether a politician is a woman compared to a man. In the second experiment that uses a single vignette design to assess these mechanisms, we also asked respondents to rate the level of toxicity of the social media conversation on a scale from 0 (low) to 10 (high). This allows us to assess (1) whether the main results from the paired conjoint design are replicable with the single vignette design, and (2) whether the mechanisms of interest are, as would be expected, associated with respondents' perceptions of the toxicity of the interaction between a politician and citizen shown in each vignette.

In [Table G14](#), we present results from an OLS regression model where the outcome is a respondent's rating of the toxicity of a conversation, and the predictors are the treatment conditions, as well as the mechanisms of interest. To ease comparison, we scale the mechanism predictors in terms of standard deviations. As Model (1) shows, consistent with the main results from the paired conjoint design, a woman politician being the target of an attack causes the toxicity of that attack to be rated higher than an otherwise equivalent attack on a man politician. As in the main results from the paired conjoint design, if the text of the attack is gender, and if the user is a man, the toxicity of a conversation is rated higher. Unlike the null effects in the main article, respondents assess attacks on co-partisans are more toxic than otherwise equivalent attacks on out-partisans. We note, however, that these results for the single conjoint design were not pre-registered.

In Models 2 and 3, we test whether the mechanisms of interest are associated with higher ratings of the toxicity of a conversation. We show both between-respondent (Model 2) and within-respondent (Model 3) models, which show similar results. As would be expected, when a respondent perceives the motives of a user sending a toxic message as driven by prejudice or to discourage the politician from being in politics, the conversation is perceived as more toxic. Perceiving the motives as driven by opinion differences is also associated with an increase in perceptions of the toxicity of an exchange, but the magnitude of the relationship is small compared to that of the other two mechanisms, and is effectively zero

if we account for within-respondent differences.

	(1)	(2)	(3)
Woman politician	0.259*** (0.042)	0.179*** (0.041)	0.166*** (0.038)
Co-partisan	0.224*** (0.064)	0.146* (0.061)	-0.012 (0.059)
Gendered text	0.321*** (0.043)	0.240*** (0.041)	0.220*** (0.037)
Man user	0.110** (0.042)	0.054 (0.040)	0.040 (0.037)
Motivated by prejudice		0.710*** (0.027)	0.443*** (0.032)
To discourage politician from being in politics		0.216*** (0.026)	0.272*** (0.032)
Opinion difference with politician		0.095*** (0.026)	0.002 (0.028)
N	15,156	14,878	14,878
Respondent FE			✓

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G14: Relationship between gender-based mechanisms and respondents’ rating of the toxicity of a social media interaction (single vignette design). Standard errors, in parentheses, are clustered at the level of the respondent. * $p < .05$, ** $p < 0.01$, *** $p < 0.001$

H Mechanism results for women and men samples

In the main article, we investigate whether the gender of a politician being targeted with toxic behavior affects assessments of a perpetrator’s motivations. Understanding these effects separately for women politicians, however, allows us to demonstrate that women who (may) face this toxicity themselves understand this behavior as a result of gender-based prejudices. It can suggest, in other words, that when women politicians experience similar toxic behaviors, they will be more likely to interpret it both as being driven by prejudice and a desire to push them out of office, compared to otherwise equivalent attacks on men politicians. And as Figure 5 in the main article shows, they interpret attacks on women

politicians as more toxic than equivalent attacks on men.

Thus, in [Figure H8](#) we show the effects of the gender of a politician on perceptions of the motivations of the perpetrator, for women and men politician respondents separately. As the figure shows, the effect of a woman politician being attacked (compared to a man) increases beliefs that the perpetrator is motivated by prejudice and a desire to push the woman politician from being in politics. We find, moreover, that the magnitude of the effect of the target being a woman on beliefs that the perpetrator is motivated by prejudice is two times as large for women politician respondents than men politician respondents ($p = 0.05$). We note that this result is exploratory, and was not part of the formal pre-registered design, however.

Finally, in [Figure H9](#), we present estimates of the effect of the target of an attack being a woman politician (compared to a man), separately for women and men citizens. Similar to those for politicians, women citizens are more likely than men citizens to perceive attacks on women politicians as driven by prejudice and a desire to push a politician out of office (although the differences are not statistically significant).

I Triple interaction hypotheses

In the Results sub-section regarding the paired conjoint design, we note that we also test four hypotheses that involve investigating whether the effect of a politician being a woman rather than a man depends on pairs of moderators. Specifically we test whether the effect of a politician being a woman on perceptions of toxicity depends on (1) whether the user sending the toxic message is a man and the respondent is a woman (i.e. whether women respondents are more sensitive to women politicians being attacked by men); (2) whether the user sending the toxic message is a man and the respondent is on the ideological left (i.e. whether left-wing respondents are more sensitive to women politicians being attacked by men); (3) whether the user sending the toxic message is a man and the message indicates

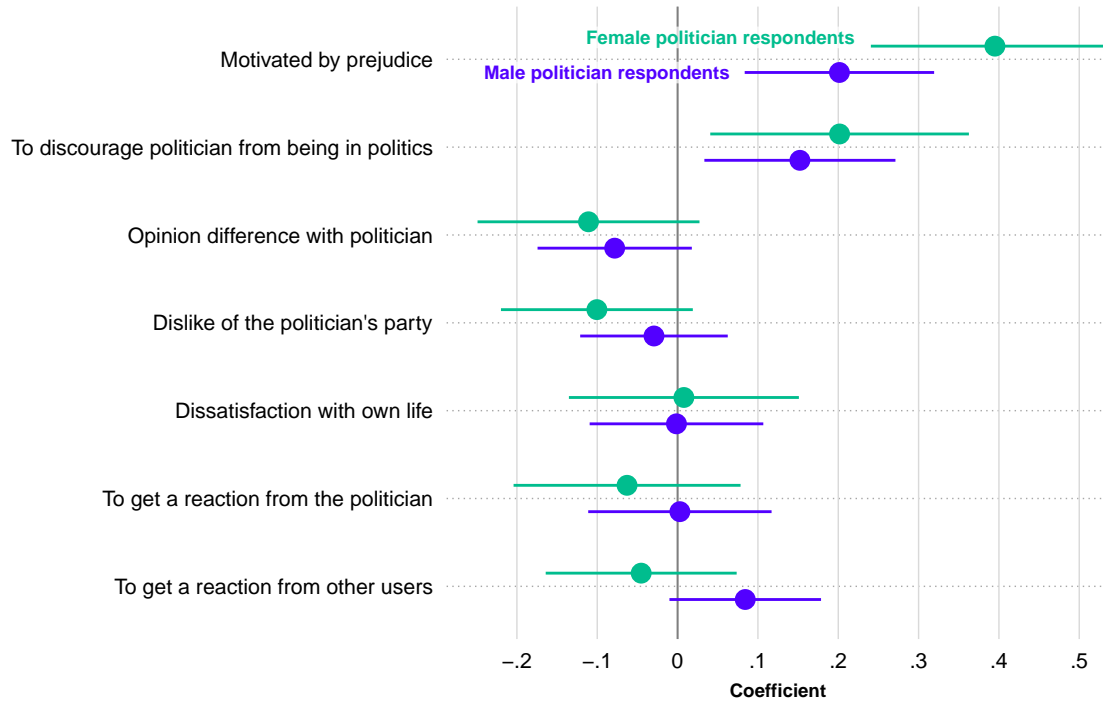


Figure H8: Effects of a targeted politician being a woman on perceptions of the motivations behind a toxic message (estimated separately for men and women politician respondents)

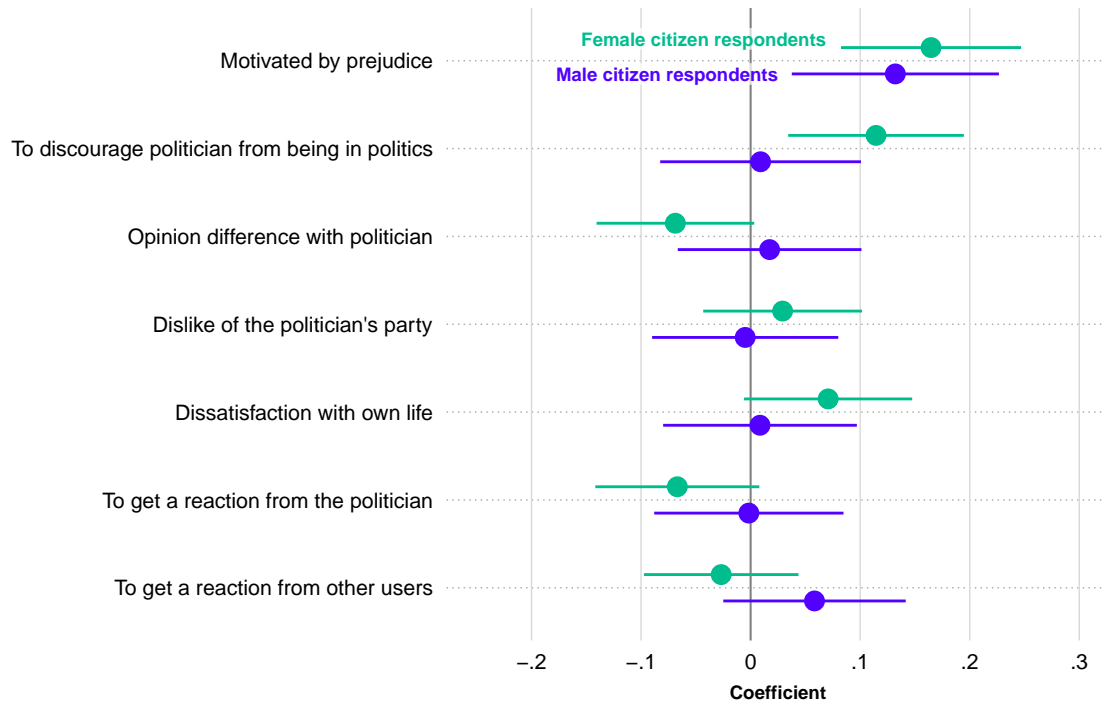


Figure H9: Effects of a targeted politician being a woman on perceptions of the motivations behind a toxic message (estimated separately for men and women citizen respondents)

the gender of the politician (i.e. whether attacks by men are considered especially toxic if the attack is also gendered); and (4) whether the message indicates the gender of the politician and the respondent is a woman (i.e. whether women respondents are more sensitive to attacks on politicians with gendered language).

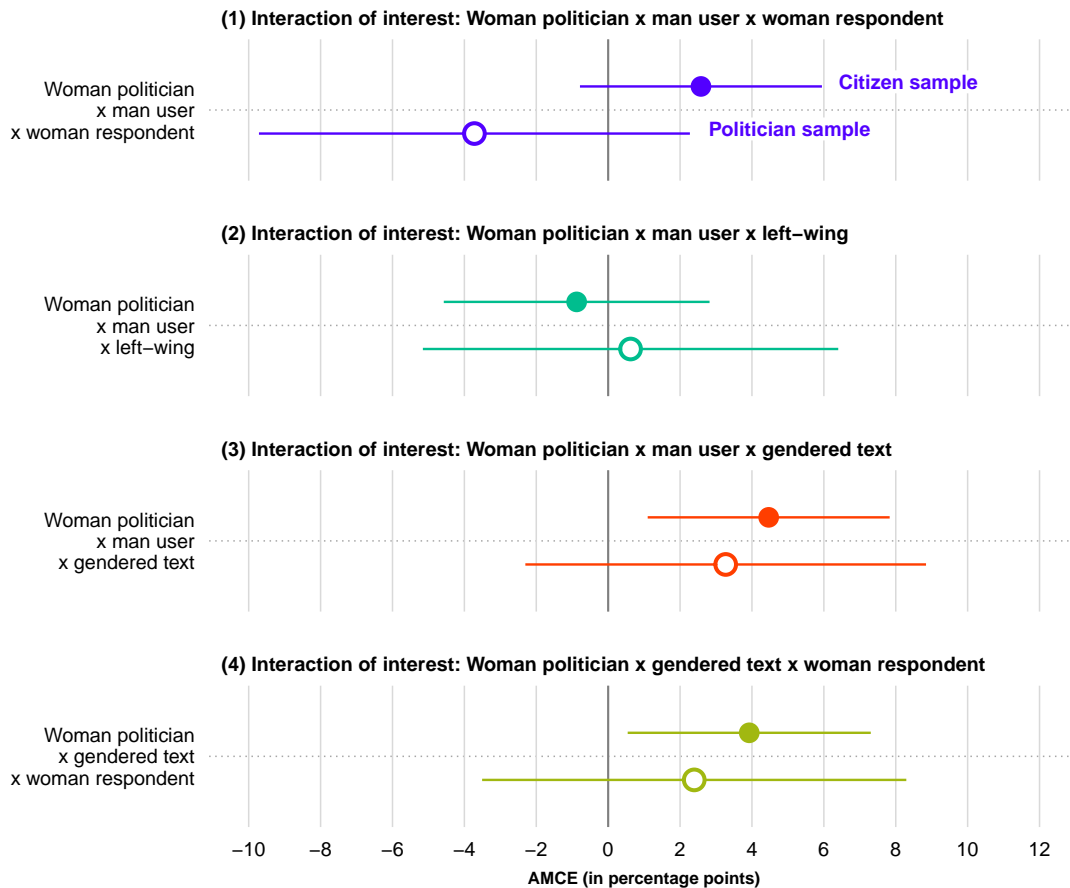


Figure I10: Triple interaction effects of a politician’s gender on perceptions of toxicity. This figure presents point estimates and 95% confidence intervals for the triple interaction terms for the sets of attributes of interest as described in this section. Models include all treatment indicators, and all relevant (double) interaction terms for the variables included in the triple interaction. Robust standard errors are clustered at the level of the respondent.

To test these, we include triple interaction terms in the models for the paired conjoint data for both politician and citizens respondents. Figure I10 shows the interaction terms that test the expectations noted above, where each coefficient in the figure is from a separate model. For clarity, coefficients for the component terms and component (double) interaction terms are not shown. As the figure shows, there is relatively weak evidence that the effect of

an attack on a politician who is a woman compared to a politician who is a man, when the attack is gendered, is stronger among women respondents (row 4) and when the attacker is a user who is a man (row 3). In both cases, although the estimates for citizens and politician respondents are the same in direction and of similar magnitude, the interaction effects are only significant for citizens. We note, however, that triple interaction terms are especially demanding of the data, and thus estimates, in general, are imprecise.

J Social desirability bias and demand effects

As we note in the main article, one of the benefits of conjoint experiments for estimating the effects of potentially sensitive traits is that by design this type of experiment helps minimize social desirability bias (Horiuchi, Markovich and Yamamoto, 2022). As Horiuchi, Markovich and Yamamoto (2022) show, fully randomized conjoint designs, as we use in our paired conjoint design, show much less evidence of social desirability bias than a partially randomized design, i.e. one in which a sensitive trait is more prominent by being varied in every pair of images/profiles. In other words, in the fully randomized design (used herein), respondents had equal probabilities in any given paired conjoint task of seeing attacks on politicians who are both women, both men, or one man and one woman.

One can nevertheless also investigate this empirically to the extent that if respondents learn the purpose of the experiment, we can expect that they may increasingly respond in a socially desirable way, i.e. show evidence of being increasingly likely to select as more toxic a conversation in which a woman politician is attacked. Although Mummolo and Peterson (2019) show that demand effects are null to minimal in survey-experimental research, evidence of changes in the effect of a woman politician would also be consistent with potential demand effects.

We investigate these possibilities by including terms in our main regression model that interact the task number that a respondent is completing and whether a politician is a

woman. This tests whether respondents are more likely to select the conversation with a woman politician in later tasks compared to the first conjoint task that they see/complete. For completeness, we fit this model both for the paired conjoint design and the vignette experiment—in which respondents were asked to rate on a scale from 0-10 how toxic a conversation is.

Results are presented in [Figure J11](#) (paired conjoint) and [Figure J12](#) (single vignette). They show that the effect of a woman politician on perceptions of toxicity for later tasks is not significantly larger than its effect for the first conjoint task that is completed by a respondent. In other words, we find no evidence that respondents learn the goals of the study or realize what the socially desirable response is, and then respond in a way consistent with social desirability bias or demand effects.

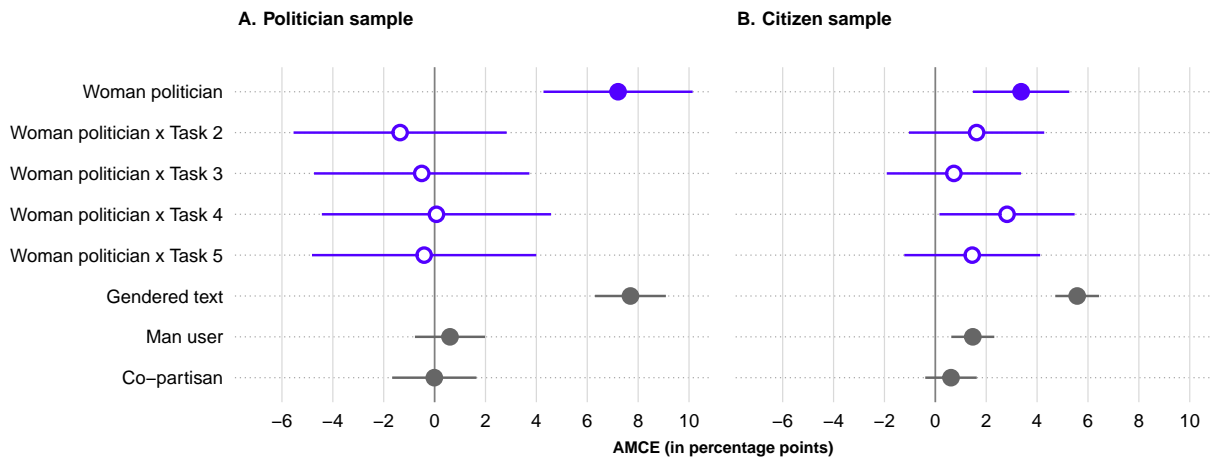


Figure J11: Effects of a politician’s gender on perceptions of toxicity conditional task number (paired conjoint)

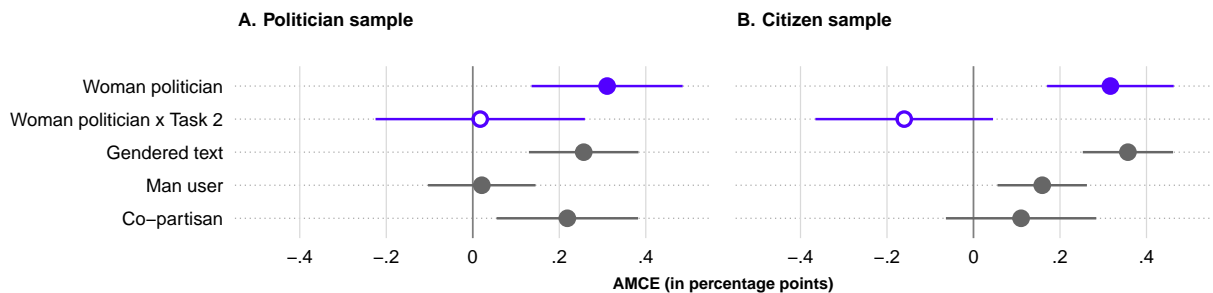


Figure J12: Effects of a politician’s gender on perceptions of toxicity conditional task number (vignette)

K Results by local and national politician samples

The sample of politicians in the experiments are those from both local and national elected office. In general, one might expect that national-level politicians are exposed to more toxic behavior on social media than are local politicians. On the other hand, local politicians are often those who aim to enter national politics, and thus are a key group of interest. To test whether the experimental effects differ by these two groups of politicians, we run separate conjoint analyses for each group. Results are presented in [Figure K13](#). They show that, in general, the magnitude of the effects are similar between local and national politicians, with no significant differences in effect sizes. We note that national-level politicians are many fewer in the sample than local-level politicians, however, which is why the confidence intervals are substantially larger for national politicians.

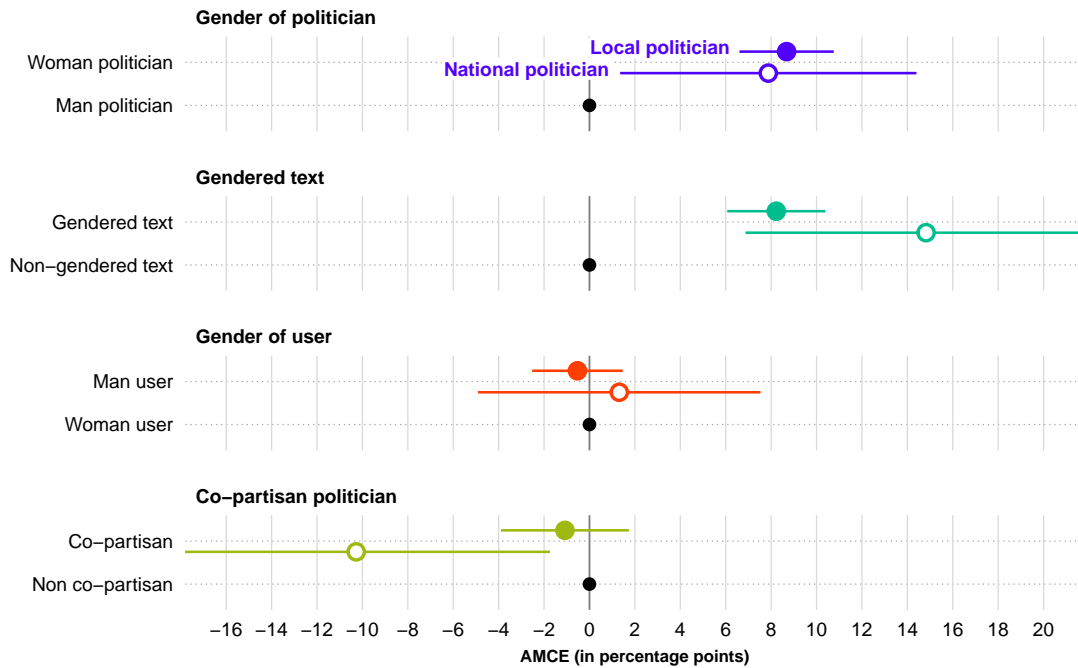


Figure K13: Effects of a politician's gender on perceptions of toxicity (local and national politician samples)

L Results by whether politician is a person of color

Our focus in the article is on differences in assessments of toxic behavior based on gendered characteristics of a conversation involving a politician being attacked on social media: a politician’s gender; the gender of the perpetrator; whether the text is gendered; and an examination of the mechanisms involved. However, although the images of politicians were held constant across the four country contexts, the images nevertheless included politicians who, visually, are either persons of color or white. Of the twelve images of politicians (per gender), four women politicians and four men politicians are persons of color (Asian, South Asian, Black). Although the names of politicians were not selected to denote racial/ethnic distinctions (unlike gender), we can conduct an exploratory analysis to test whether attacks on politicians who are persons of color (as shown by their photo) are likely to be perceived as more toxic than otherwise equivalent attacks on politicians who are white.

Results are presented in [Figure L14](#). They show that, among politician respondents, otherwise equivalent messages that attack politicians who are persons of color are understood as more toxic than those attacking politicians who are white ($p < 0.01$). No statistically differences are observed among citizen respondents. These results suggest that the main findings in the article may extend to politicians from other under-represented or non-dominant political groups. Whether these effects are more pronounced when the race of politicians or ethnicity of their name are also signaled in an analogous social media conversations to those in this article represents an important avenue for research in the future.

M Results for the text of posts by politicians

In [subsection A.2](#), we describe the process we used to develop the texts of the social media posts made by politicians. Because we use these texts across 4 country contexts, the topics of these texts may have differential effects on perceptions of toxicity of conversations, given the focus of politics in each country at the time. The topics of these texts may also moderate

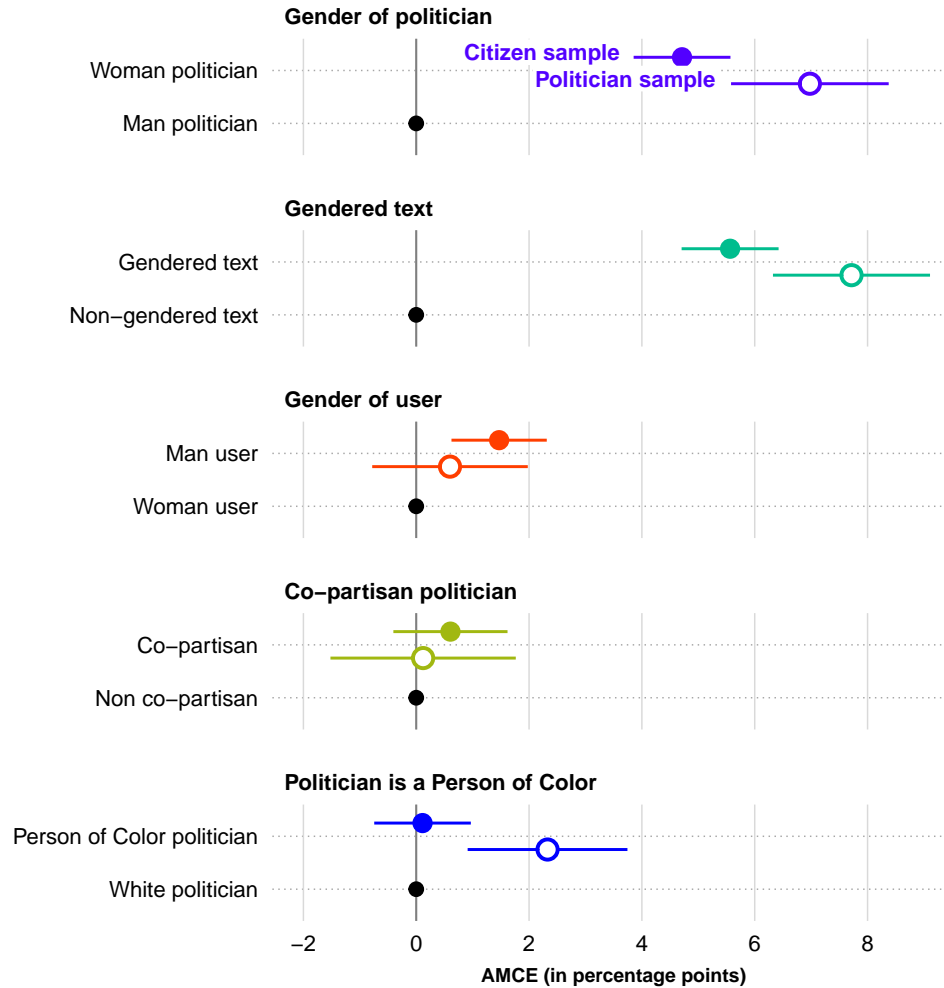


Figure L14: Effects of a politician’s race (as denoted by the image in their social media profile) on perceptions of toxicity

the effect of whether the politician making the post is a woman or a man. We test this by creating binary variables that indicate the topic of each text and including them in our main regression model independently, and interacted with whether a politician is a woman or a man.

Results are presented in [Figure M15](#) and [Figure M16](#). As the results in show, for each country the topic of a politician’s social media post affects neither politicians’ nor citizens’ assessments of the toxicity of conversations, with no meaningful differences across countries. In [Table N15](#) of [Appendix N](#), we also show that the *individual* texts of the social media posts by politicians show no systematic patterns within or across country contexts (4% of all the 152

coefficients for the text of posts by politicians are significant, of which 5% would be expected given the multiple comparisons). The results for the interactions between politicians' gender and the topic of their social media posts are shown in [Figure M16](#). The figure demonstrates that the effect of a woman politician is not meaningfully different depending on the topic of the social media post that they send in each country.

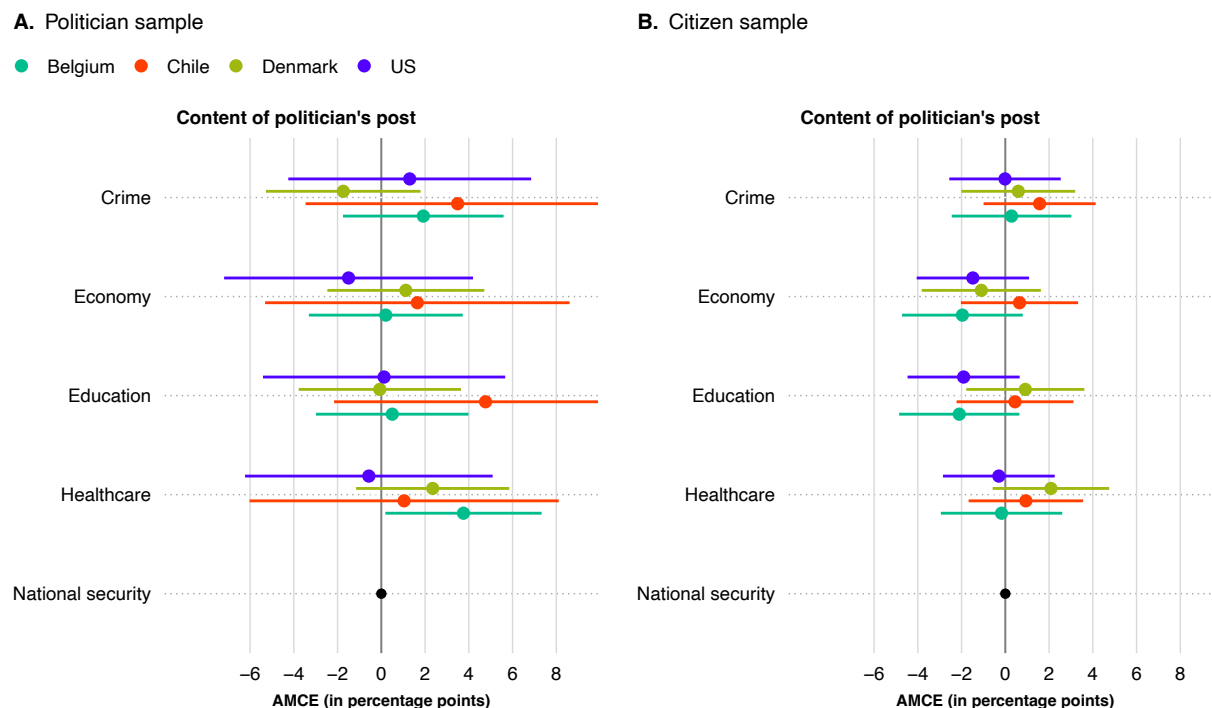


Figure M15: Effects of content of politicians' social media posts on perceptions of toxicity.

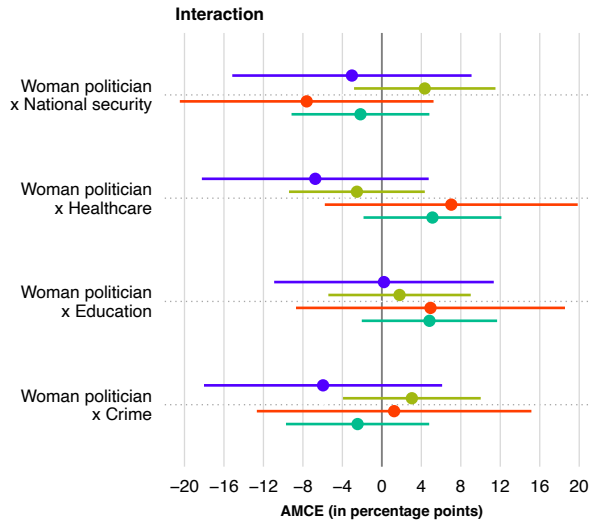
N Complete regression model results

In the main article, Figures 3, 4, 5, 6, and 7 do not present all coefficients from the each model: excluded from the models are treatment indicators for the 20 social media texts (valence issue statements) by politicians and 16 social media texts (toxic messages) by users. In this section, we present all coefficients from each of these models. In each table, the politician and user text numbers refer to those as shown and ordered in [subsection A.2](#).

Complete regression results for Figure 3 in the main article are presented in [Table N15](#);

A. Politician sample

● Belgium ● Chile ● Denmark ● US



B. Citizen sample

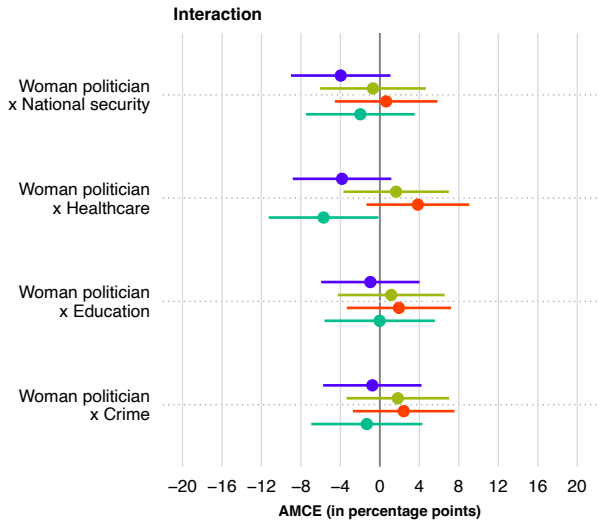


Figure M16: Effects of a politician’s gender on perceptions of toxicity conditional on issue type (by country). The baseline category for the topic variable is “Economy”.

complete results for Figure 4 in [Table N16](#); complete results for Figure 5 in [Table N17](#) (politician sample) and [Table N18](#) (citizen sample); complete results from Figure 6 in [Table N19](#) (politician sample) and [Table N20](#) (citizen sample); and complete results from Figure 7 in [Table N21](#).

Table N16: Complete regression results for Figure 4 in the main article

	Politicians	Citizens	Politicians	Citizens
Woman politician × gendered text	0.085*** (0.014)	0.066*** (0.009)		
Woman politician × man user			0.052*** (0.015)	0.031*** (0.008)
Woman politician	0.025* (0.010)	0.014* (0.006)	0.041*** (0.010)	0.031*** (0.006)
Gendered text	0.034*** (0.010)	0.023*** (0.006)	0.077*** (0.007)	0.056*** (0.004)
Man user	0.006 (0.007)	0.015*** (0.004)	-0.020* (0.010)	-0.001 (0.006)
Co-partisan	0.001 (0.008)	0.006 (0.005)	0.001 (0.008)	0.006 (0.005)
Politician text 2	-0.005 (0.023)	0.008 (0.013)	-0.007 (0.023)	0.008 (0.013)
Politician text 3	-0.006 (0.022)	0.019 (0.014)	-0.006 (0.022)	0.020 (0.014)
Politician text 4	-0.012 (0.023)	0.021 (0.013)	-0.013 (0.023)	0.022 (0.013)
Politician text 5	0.028 (0.023)	0.038** (0.014)	0.027 (0.023)	0.038** (0.014)
Politician text 6	0.005 (0.023)	0.027* (0.013)	0.003 (0.023)	0.028* (0.013)
Politician text 7	0.006 (0.022)	0.029* (0.014)	0.004 (0.022)	0.029* (0.014)
Politician text 8	0.021 (0.023)	0.020 (0.014)	0.019 (0.023)	0.020 (0.014)
Politician text 9	0.002 (0.023)	0.015 (0.013)	0.001 (0.023)	0.015 (0.013)
Politician text 10	0.020 (0.023)	0.003 (0.013)	0.018 (0.023)	0.004 (0.013)
Politician text 11	-0.019 (0.023)	0.016 (0.014)	-0.020 (0.023)	0.017 (0.014)
Politician text 12	-0.018 (0.022)	0.027* (0.014)	-0.019 (0.022)	0.028* (0.014)
Politician text 13	0.013 (0.023)	0.026 (0.013)	0.011 (0.023)	0.026 (0.013)
Politician text 14	-0.001 (0.023)	0.039** (0.014)	-0.003 (0.023)	0.041** (0.014)
Politician text 15	-0.030 (0.022)	0.025 (0.013)	-0.032 (0.022)	0.025 (0.013)
Politician text 16	0.010 (0.022)	0.021 (0.013)	0.010 (0.022)	0.022 (0.013)
Politician text 17	-0.017 (0.022)	0.030* (0.014)	-0.018 (0.022)	0.031* (0.014)
Politician text 18	-0.006 (0.022)	0.024 (0.013)	-0.007 (0.023)	0.024 (0.013)
Politician text 19	-0.011 (0.022)	0.015 (0.013)	-0.012 (0.022)	0.015 (0.013)
Politician text 20	-0.004 (0.023)	0.021 (0.013)	-0.006 (0.023)	0.021 (0.013)
User text 2	-0.109*** (0.020)	-0.025* (0.012)	-0.110*** (0.020)	-0.025* (0.012)
User text 3	0.063** (0.021)	0.055*** (0.012)	0.062** (0.021)	0.055*** (0.012)
User text 4	-0.001 (0.021)	0.046*** (0.012)	-0.002 (0.021)	0.047*** (0.012)
User text 5	-0.115*** (0.021)	-0.120*** (0.012)	-0.116*** (0.021)	-0.120*** (0.012)
User text 6	-0.039 (0.021)	0.016 (0.013)	-0.040 (0.021)	0.016 (0.013)
User text 7	-0.167*** (0.020)	-0.091*** (0.012)	-0.168*** (0.020)	-0.091*** (0.012)
User text 8	0.041 (0.021)	-0.022 (0.013)	0.040 (0.021)	-0.022 (0.013)
User text 9	-0.143*** (0.020)	-0.078*** (0.012)	-0.144*** (0.020)	-0.078*** (0.012)
User text 10	-0.032 (0.021)	0.032* (0.012)	-0.033 (0.021)	0.031* (0.012)
User text 11	0.082*** (0.021)	-0.029* (0.013)	0.082*** (0.021)	-0.029* (0.013)
User text 12	-0.155*** (0.021)	-0.177*** (0.012)	-0.157*** (0.021)	-0.177*** (0.012)
User text 13	0.049* (0.020)	0.007 (0.013)	0.047* (0.020)	0.007 (0.013)
User text 14	0.138*** (0.021)	-0.016 (0.013)	0.136*** (0.021)	-0.016 (0.013)
User text 15	0.086*** (0.020)	0.127*** (0.012)	0.085*** (0.020)	0.126*** (0.012)
User text 16	-0.002 (0.021)	-0.020 (0.013)	-0.003 (0.021)	-0.020 (0.013)
N observations	19,012	53,630	19,012	53,630
N respondents	2,153	5,371	2,153	5,371

* p < 0.05, ** p < 0.01, *** p < 0.001

Table N17: Complete regression results for Figure 5 in the main article (*politician* sample)

	Gender		Ideology		Partisanship		Experience with harassment	
	Women	Men	Right-wing	Left-wing	Co-partisan	Out-partisan	Experience with harassment	No experience with harassment
Woman politician	0.084*** (0.012)	0.055*** (0.009)	0.062*** (0.011)	0.078*** (0.011)	0.080*** (0.016)	0.063*** (0.008)	0.070*** (0.009)	0.062*** (0.012)
Gendered text	0.086*** (0.012)	0.068*** (0.009)	0.072*** (0.011)	0.083*** (0.011)	0.068*** (0.016)	0.079*** (0.008)	0.082*** (0.009)	0.068*** (0.011)
Man user	0.001 (0.011)	0.009 (0.009)	0.024* (0.011)	-0.002 (0.011)	0.008 (0.016)	0.006 (0.008)	0.004 (0.009)	0.009 (0.011)
Co-partisan	-0.002 (0.014)	0.000 (0.011)	0.005 (0.013)	-0.003 (0.013)			0.008 (0.010)	-0.012 (0.015)
Politician text 2	-0.017 (0.037)	0.001 (0.029)	0.059 (0.035)	-0.050 (0.035)	0.001 (0.054)	-0.008 (0.025)	-0.041 (0.029)	0.050 (0.037)
Politician text 3	-0.006 (0.038)	-0.005 (0.028)	0.003 (0.035)	-0.033 (0.034)	-0.051 (0.051)	0.004 (0.025)	-0.041 (0.028)	0.053 (0.035)
Politician text 4	0.000 (0.039)	-0.023 (0.030)	0.005 (0.035)	-0.031 (0.036)	-0.034 (0.053)	-0.009 (0.025)	-0.039 (0.029)	0.030 (0.037)
Politician text 5	0.037 (0.036)	0.017 (0.030)	0.050 (0.036)	-0.025 (0.034)	0.061 (0.053)	0.019 (0.025)	0.001 (0.029)	0.072* (0.037)
Politician text 6	0.029 (0.038)	-0.018 (0.029)	0.005 (0.034)	-0.024 (0.036)	-0.038 (0.054)	0.013 (0.025)	-0.044 (0.029)	0.079* (0.037)
Politician text 7	0.018 (0.036)	-0.003 (0.029)	0.037 (0.034)	-0.025 (0.035)	0.030 (0.053)	-0.003 (0.025)	-0.022 (0.028)	0.050 (0.036)
Politician text 8	-0.012 (0.038)	0.038 (0.029)	0.051 (0.035)	0.006 (0.035)	-0.010 (0.052)	0.028 (0.025)	-0.007 (0.029)	0.067 (0.037)
Politician text 9	-0.021 (0.040)	0.014 (0.029)	0.040 (0.036)	-0.057 (0.035)	-0.008 (0.052)	0.004 (0.026)	-0.030 (0.029)	0.055 (0.039)
Politician text 10	0.038 (0.038)	0.009 (0.029)	0.071* (0.036)	-0.020 (0.035)	0.004 (0.053)	0.022 (0.025)	0.022 (0.029)	0.011 (0.037)
Politician text 11	-0.031 (0.037)	-0.022 (0.030)	0.006 (0.036)	-0.042 (0.035)	-0.003 (0.053)	-0.024 (0.026)	-0.005 (0.029)	-0.034 (0.037)
Politician text 12	0.004 (0.037)	-0.035 (0.028)	0.013 (0.033)	-0.067* (0.034)	-0.109* (0.051)	0.004 (0.025)	-0.044 (0.028)	0.022 (0.035)
Politician text 13	0.032 (0.037)	0.002 (0.030)	0.030 (0.036)	0.014 (0.035)	0.022 (0.051)	0.007 (0.026)	-0.010 (0.030)	0.045 (0.036)
Politician text 14	0.005 (0.038)	-0.009 (0.029)	0.026 (0.035)	-0.036 (0.034)	-0.017 (0.052)	0.000 (0.025)	-0.025 (0.029)	0.037 (0.036)
Politician text 15	-0.044 (0.038)	-0.021 (0.028)	-0.007 (0.033)	-0.068 (0.035)	-0.046 (0.050)	-0.027 (0.025)	-0.054 (0.029)	0.004 (0.035)
Politician text 16	-0.025 (0.038)	0.030 (0.028)	0.062 (0.034)	-0.027 (0.034)	0.012 (0.053)	0.010 (0.025)	-0.007 (0.029)	0.044 (0.035)
Politician text 17	-0.012 (0.038)	-0.019 (0.029)	0.000 (0.033)	-0.025 (0.035)	-0.003 (0.049)	-0.022 (0.025)	-0.017 (0.029)	-0.018 (0.035)
Politician text 18	-0.029 (0.038)	0.003 (0.028)	0.032 (0.034)	-0.051 (0.035)	-0.066 (0.053)	0.009 (0.025)	-0.032 (0.029)	0.034 (0.035)
Politician text 19	0.002 (0.037)	-0.015 (0.028)	-0.003 (0.033)	-0.026 (0.036)	-0.025 (0.052)	-0.008 (0.025)	-0.029 (0.029)	0.017 (0.035)
Politician text 20	-0.024 (0.040)	0.008 (0.029)	0.044 (0.034)	-0.057 (0.037)	-0.030 (0.053)	0.000 (0.026)	-0.021 (0.029)	0.018 (0.038)
User text 2	-0.114*** (0.033)	-0.109*** (0.026)	-0.152*** (0.031)	-0.069* (0.031)	-0.114** (0.044)	-0.109*** (0.023)	-0.065* (0.026)	-0.181*** (0.033)
User text 3	0.087* (0.035)	0.045 (0.027)	0.048 (0.034)	0.064* (0.032)	0.121** (0.046)	0.047* (0.024)	0.097*** (0.026)	0.004 (0.035)
User text 4	0.070* (0.034)	-0.044 (0.027)	-0.015 (0.032)	0.015 (0.033)	0.014 (0.045)	-0.006 (0.024)	0.032 (0.027)	-0.054 (0.034)
User text 5	-0.057 (0.033)	-0.149*** (0.028)	-0.162*** (0.033)	-0.072* (0.032)	-0.097* (0.045)	-0.120*** (0.023)	-0.083** (0.026)	-0.167*** (0.034)
User text 6	-0.006 (0.033)	-0.060* (0.027)	-0.057 (0.033)	-0.021 (0.031)	0.009 (0.046)	-0.052* (0.023)	-0.006 (0.026)	-0.097** (0.034)
User text 7	-0.118*** (0.034)	-0.198*** (0.026)	-0.203*** (0.032)	-0.156*** (0.031)	-0.132** (0.045)	-0.179*** (0.022)	-0.151*** (0.026)	-0.198*** (0.032)
User text 8	0.128*** (0.035)	-0.013 (0.027)	0.047 (0.032)	0.032 (0.032)	0.018 (0.046)	0.045 (0.023)	0.053* (0.027)	0.018 (0.034)
User text 9	-0.111** (0.034)	-0.169*** (0.026)	-0.168*** (0.032)	-0.135*** (0.031)	-0.115** (0.044)	-0.153*** (0.023)	-0.133*** (0.025)	-0.163*** (0.034)
User text 10	0.001 (0.036)	-0.052 (0.027)	-0.043 (0.032)	-0.050 (0.033)	0.023 (0.045)	-0.049* (0.023)	0.006 (0.026)	-0.098** (0.034)
User text 11	0.086* (0.035)	0.078** (0.027)	0.068* (0.033)	0.081* (0.033)	0.115* (0.045)	0.073** (0.024)	0.114*** (0.027)	0.034 (0.034)
User text 12	-0.063 (0.035)	-0.210*** (0.026)	-0.161*** (0.032)	-0.155*** (0.031)	-0.174*** (0.043)	-0.153*** (0.024)	-0.140*** (0.026)	-0.179*** (0.034)
User text 13	0.093** (0.033)	0.019 (0.027)	0.028 (0.032)	0.073* (0.030)	0.081 (0.043)	0.039 (0.023)	0.056* (0.026)	0.032 (0.032)
User text 14	0.136*** (0.035)	0.145*** (0.027)	0.143*** (0.032)	0.145*** (0.033)	0.169*** (0.044)	0.128*** (0.024)	0.168*** (0.027)	0.087** (0.034)
User text 15	0.109** (0.034)	0.072** (0.026)	0.093** (0.032)	0.060 (0.031)	0.065 (0.045)	0.091*** (0.023)	0.112*** (0.026)	0.043 (0.033)
User text 16	0.053 (0.035)	-0.032 (0.028)	-0.046 (0.033)	0.028 (0.032)	0.021 (0.046)	-0.009 (0.024)	0.015 (0.027)	-0.031 (0.034)
N observations	7,008	11,406	7,868	8,086	3,708	15,304	11,574	7,438
N respondents	776	1,272	875	891	1,230	2,142	1,291	862

* p < 0.05, ** p < 0.01, *** p < 0.001

Table N18: Complete regression results for Figure 5 in the main article (*citizen* sample)

	Gender		Ideology		Partisanship		Experience with harassment	
	Women	Men	Right-wing	Left-wing	Co-partisan	Out-partisan	Experience with harassment	No experience with harassment
Woman politician	0.053*** (0.006)	0.040*** (0.006)	0.044*** (0.007)	0.051*** (0.008)	0.039*** (0.011)	0.048*** (0.005)	0.050*** (0.006)	0.043*** (0.007)
Gendered text	0.068*** (0.006)	0.041*** (0.007)	0.051*** (0.007)	0.062*** (0.008)	0.048*** (0.011)	0.057*** (0.005)	0.052*** (0.006)	0.061*** (0.007)
Man user	0.010 (0.006)	0.020** (0.007)	0.011 (0.007)	0.026** (0.008)	0.029** (0.011)	0.012** (0.005)	0.011 (0.006)	0.020** (0.007)
Co-partisan	-0.009 (0.007)	0.022** (0.008)	0.005 (0.008)	0.001 (0.010)			0.004 (0.007)	0.009 (0.008)
Politician text 2	0.001 (0.018)	0.017 (0.020)	0.030 (0.022)	0.015 (0.026)	0.012 (0.035)	0.007 (0.015)	0.007 (0.017)	0.009 (0.021)
Politician text 3	0.025 (0.018)	0.010 (0.021)	0.025 (0.022)	0.012 (0.027)	0.063 (0.035)	0.012 (0.015)	0.025 (0.017)	0.012 (0.021)
Politician text 4	0.038* (0.018)	-0.002 (0.020)	0.021 (0.022)	0.033 (0.026)	0.005 (0.034)	0.024 (0.014)	0.024 (0.017)	0.024 (0.021)
Politician text 5	0.043* (0.018)	0.030 (0.021)	0.034 (0.022)	0.053* (0.027)	0.061 (0.035)	0.034* (0.015)	0.045* (0.018)	0.030 (0.021)
Politician text 6	0.031 (0.018)	0.025 (0.020)	0.036 (0.022)	0.045 (0.026)	0.026 (0.035)	0.028 (0.014)	0.025 (0.017)	0.033 (0.021)
Politician text 7	0.019 (0.018)	0.041* (0.020)	0.038 (0.022)	0.030 (0.026)	-0.003 (0.035)	0.034* (0.015)	0.020 (0.018)	0.042* (0.021)
Politician text 8	0.041* (0.018)	-0.009 (0.021)	0.039 (0.022)	0.014 (0.028)	0.047 (0.036)	0.015 (0.015)	0.032 (0.018)	0.003 (0.022)
Politician text 9	0.035 (0.018)	-0.011 (0.020)	0.018 (0.022)	0.035 (0.026)	0.013 (0.034)	0.015 (0.015)	0.008 (0.017)	0.026 (0.021)
Politician text 10	0.005 (0.018)	0.004 (0.021)	0.014 (0.023)	0.022 (0.026)	0.003 (0.034)	0.003 (0.015)	-0.008 (0.017)	0.023 (0.022)
Politician text 11	0.028 (0.018)	-0.001 (0.020)	0.038 (0.023)	-0.009 (0.026)	0.001 (0.034)	0.019 (0.015)	0.032 (0.017)	-0.006 (0.022)
Politician text 12	0.037* (0.018)	0.016 (0.021)	0.045* (0.022)	0.019 (0.027)	0.064 (0.034)	0.020 (0.015)	0.024 (0.017)	0.031 (0.022)
Politician text 13	0.031 (0.018)	0.019 (0.021)	0.033 (0.022)	0.026 (0.026)	-0.032 (0.034)	0.036* (0.015)	0.020 (0.017)	0.036 (0.021)
Politician text 14	0.054** (0.018)	0.023 (0.021)	0.060** (0.022)	0.018 (0.027)	0.013 (0.035)	0.045** (0.015)	0.043* (0.017)	0.037 (0.021)
Politician text 15	0.031 (0.018)	0.018 (0.020)	0.055* (0.022)	0.019 (0.026)	0.041 (0.034)	0.022 (0.015)	0.026 (0.017)	0.022 (0.021)
Politician text 16	0.018 (0.018)	0.022 (0.020)	0.039 (0.021)	0.037 (0.026)	0.011 (0.034)	0.024 (0.014)	0.023 (0.017)	0.022 (0.021)
Politician text 17	0.020 (0.018)	0.045* (0.021)	0.053* (0.023)	0.058* (0.027)	0.064 (0.036)	0.025 (0.015)	0.035* (0.018)	0.024 (0.022)
Politician text 18	0.023 (0.018)	0.027 (0.020)	0.050* (0.022)	0.035 (0.026)	0.054 (0.037)	0.020 (0.015)	0.014 (0.017)	0.039 (0.021)
Politician text 19	0.001 (0.018)	0.031 (0.020)	0.032 (0.023)	0.015 (0.026)	0.019 (0.034)	0.014 (0.015)	0.001 (0.017)	0.035 (0.021)
Politician text 20	0.026 (0.018)	0.012 (0.020)	0.052* (0.022)	0.016 (0.026)	0.035 (0.036)	0.018 (0.014)	0.022 (0.017)	0.020 (0.022)
User text 2	-0.013 (0.016)	-0.041* (0.018)	-0.034 (0.020)	-0.028 (0.023)	-0.053 (0.031)	-0.020 (0.013)	-0.006 (0.016)	-0.053** (0.019)
User text 3	0.069*** (0.017)	0.038* (0.018)	0.014 (0.020)	0.083*** (0.024)	0.079* (0.033)	0.052*** (0.013)	0.058*** (0.016)	0.052** (0.020)
User text 4	0.083*** (0.017)	0.001 (0.019)	0.032 (0.021)	0.043 (0.024)	0.042 (0.032)	0.047*** (0.014)	0.071*** (0.016)	0.009 (0.020)
User text 5	-0.091*** (0.017)	-0.160*** (0.019)	-0.132*** (0.020)	-0.130*** (0.024)	-0.113*** (0.032)	-0.121*** (0.013)	-0.096*** (0.016)	-0.156*** (0.020)
User text 6	0.025 (0.017)	0.002 (0.019)	0.003 (0.021)	0.013 (0.024)	0.018 (0.032)	0.016 (0.014)	0.045** (0.016)	-0.028 (0.020)
User text 7	-0.080*** (0.017)	-0.109*** (0.019)	-0.103*** (0.020)	-0.103*** (0.024)	-0.082* (0.032)	-0.092*** (0.013)	-0.060*** (0.016)	-0.137*** (0.020)
User text 8	-0.005 (0.017)	-0.046* (0.019)	-0.020 (0.021)	-0.023 (0.024)	0.033 (0.033)	-0.031* (0.014)	-0.020 (0.016)	-0.025 (0.020)
User text 9	-0.068*** (0.017)	-0.093*** (0.019)	-0.080*** (0.021)	-0.079*** (0.024)	-0.118*** (0.032)	-0.072*** (0.013)	-0.054*** (0.016)	-0.114*** (0.020)
User text 10	0.043* (0.017)	0.014 (0.019)	0.027 (0.021)	0.028 (0.023)	0.076* (0.032)	0.024 (0.013)	0.034* (0.016)	0.028 (0.020)
User text 11	-0.032 (0.017)	-0.028 (0.019)	-0.050* (0.020)	0.016 (0.025)	-0.034 (0.032)	-0.028* (0.014)	-0.036* (0.016)	-0.018 (0.020)
User text 12	-0.154*** (0.016)	-0.211*** (0.018)	-0.176*** (0.020)	-0.186*** (0.023)	-0.137*** (0.032)	-0.184*** (0.013)	-0.161*** (0.016)	-0.203*** (0.019)
User text 13	0.025 (0.017)	-0.017 (0.019)	-0.005 (0.020)	0.003 (0.024)	0.006 (0.031)	0.008 (0.014)	-0.001 (0.016)	0.021 (0.020)
User text 14	-0.006 (0.017)	-0.031 (0.019)	-0.003 (0.021)	-0.012 (0.024)	0.048 (0.033)	-0.027* (0.013)	-0.025 (0.016)	-0.002 (0.020)
User text 15	0.142*** (0.016)	0.108*** (0.018)	0.113*** (0.020)	0.135*** (0.023)	0.117*** (0.031)	0.128*** (0.013)	0.140*** (0.016)	0.107*** (0.019)
User text 16	0.019 (0.017)	-0.070*** (0.019)	-0.014 (0.021)	-0.022 (0.024)	0.062 (0.032)	-0.033* (0.014)	-0.012 (0.016)	-0.031 (0.020)
N observations	29,776	23,614	19,636	14,758	7,831	45,799	32,156	21,474
N respondents	2,981	2,366	1,967	1,478	1,984	5,369	3,219	2,152

* p < 0.05, ** p < 0.01, *** p < 0.001

Table N19: Complete regression results for Figure 6 in the main article (*politician* sample)

	Prejudice	Push politician out of office	Opinion differences	Dislike politician's party	Dissatisfied with own life	Get a reaction from the politician	Get a reaction from other users
Woman politician	0.252*** (0.046)	0.154** (0.047)	-0.090* (0.039)	-0.057 (0.036)	0.026 (0.043)	-0.017 (0.044)	0.028 (0.036)
Gendered text	0.144** (0.047)	0.038 (0.047)	-0.030 (0.038)	-0.039 (0.036)	-0.049 (0.042)	-0.087* (0.044)	-0.054 (0.037)
Man user	0.075 (0.046)	-0.007 (0.046)	-0.092* (0.038)	-0.049 (0.036)	0.017 (0.043)	0.010 (0.045)	-0.057 (0.037)
Co-partisan	0.211*** (0.060)	0.034 (0.060)	0.037 (0.049)	0.109* (0.044)	0.114* (0.053)	0.101 (0.056)	0.107* (0.046)
Politician text 2	-0.002 (0.135)	0.211 (0.142)	-0.175 (0.111)	-0.055 (0.105)	0.036 (0.120)	0.096 (0.128)	-0.112 (0.103)
Politician text 3	-0.118 (0.140)	0.101 (0.137)	-0.169 (0.115)	0.072 (0.107)	0.007 (0.127)	-0.043 (0.129)	-0.147 (0.107)
Politician text 4	-0.150 (0.141)	0.040 (0.135)	-0.321** (0.112)	-0.061 (0.109)	-0.030 (0.128)	-0.062 (0.135)	-0.128 (0.104)
Politician text 5	0.045 (0.145)	0.020 (0.136)	-0.154 (0.119)	-0.009 (0.110)	0.032 (0.133)	0.013 (0.130)	-0.160 (0.102)
Politician text 6	-0.018 (0.148)	-0.020 (0.153)	-0.019 (0.118)	0.003 (0.114)	-0.192 (0.139)	0.024 (0.141)	-0.061 (0.112)
Politician text 7	-0.192 (0.147)	0.030 (0.145)	-0.368** (0.125)	-0.075 (0.115)	-0.270* (0.136)	-0.044 (0.135)	-0.163 (0.113)
Politician text 8	-0.045 (0.142)	0.171 (0.135)	-0.193 (0.112)	-0.063 (0.113)	-0.024 (0.128)	-0.126 (0.138)	-0.133 (0.105)
Politician text 9	0.059 (0.140)	0.075 (0.136)	-0.112 (0.115)	0.075 (0.104)	0.120 (0.127)	0.009 (0.132)	-0.132 (0.105)
Politician text 10	0.032 (0.140)	0.078 (0.146)	-0.360** (0.121)	0.031 (0.112)	-0.075 (0.133)	0.166 (0.133)	0.050 (0.105)
Politician text 11	-0.256 (0.142)	-0.010 (0.140)	-0.046 (0.109)	-0.009 (0.116)	-0.158 (0.129)	0.029 (0.128)	-0.080 (0.108)
Politician text 12	-0.182 (0.141)	-0.169 (0.142)	-0.050 (0.112)	0.021 (0.112)	0.032 (0.129)	-0.086 (0.134)	-0.231* (0.108)
Politician text 13	0.077 (0.142)	-0.096 (0.140)	0.027 (0.110)	0.071 (0.106)	-0.152 (0.127)	-0.017 (0.132)	0.013 (0.104)
Politician text 14	0.097 (0.138)	-0.083 (0.142)	-0.095 (0.113)	0.075 (0.111)	-0.193 (0.128)	0.066 (0.130)	-0.017 (0.099)
Politician text 15	0.049 (0.136)	-0.096 (0.137)	-0.215 (0.111)	0.004 (0.107)	-0.136 (0.127)	0.101 (0.132)	-0.190 (0.105)
Politician text 16	0.131 (0.139)	-0.073 (0.138)	-0.053 (0.110)	-0.026 (0.106)	-0.111 (0.126)	0.014 (0.129)	-0.325** (0.108)
Politician text 17	0.079 (0.140)	0.022 (0.139)	-0.159 (0.119)	0.083 (0.103)	-0.026 (0.126)	0.020 (0.133)	-0.174 (0.108)
Politician text 18	0.166 (0.141)	0.096 (0.135)	-0.238* (0.118)	-0.111 (0.110)	-0.117 (0.127)	0.058 (0.132)	-0.101 (0.102)
Politician text 19	0.150 (0.138)	0.057 (0.146)	-0.154 (0.114)	0.110 (0.106)	0.051 (0.128)	0.188 (0.133)	0.040 (0.100)
Politician text 20	-0.145 (0.135)	0.051 (0.136)	-0.079 (0.107)	0.013 (0.110)	-0.021 (0.126)	-0.064 (0.128)	-0.184 (0.103)
User text 2	-0.319* (0.128)	-0.009 (0.132)	0.065 (0.108)	-0.164 (0.100)	0.026 (0.117)	-0.129 (0.127)	-0.150 (0.102)
User text 3	-0.150 (0.122)	0.389** (0.129)	0.056 (0.103)	-0.009 (0.092)	0.049 (0.114)	-0.059 (0.123)	-0.102 (0.104)
User text 4	-0.128 (0.125)	0.207 (0.130)	0.036 (0.103)	-0.047 (0.098)	-0.068 (0.115)	0.020 (0.125)	0.031 (0.100)
User text 5	-0.219 (0.125)	0.124 (0.126)	-0.141 (0.106)	-0.206* (0.099)	0.133 (0.117)	0.099 (0.125)	-0.085 (0.106)
User text 6	-0.422** (0.131)	0.123 (0.133)	0.204 (0.106)	-0.154 (0.101)	0.014 (0.117)	-0.027 (0.134)	-0.028 (0.105)
User text 7	-0.306* (0.129)	-0.116 (0.131)	0.116 (0.108)	-0.169 (0.102)	-0.103 (0.122)	0.121 (0.124)	-0.318** (0.112)
User text 8	0.239 (0.122)	0.316* (0.130)	0.056 (0.108)	-0.100 (0.098)	0.050 (0.120)	-0.022 (0.126)	-0.095 (0.105)
User text 9	-0.306* (0.125)	0.006 (0.127)	0.051 (0.106)	-0.037 (0.095)	-0.182 (0.121)	0.028 (0.127)	0.013 (0.098)
User text 10	-0.355** (0.124)	-0.079 (0.128)	0.026 (0.104)	-0.029 (0.095)	-0.003 (0.121)	0.120 (0.125)	-0.056 (0.103)
User text 11	-0.086 (0.128)	-0.027 (0.135)	0.068 (0.113)	-0.010 (0.100)	0.173 (0.115)	0.031 (0.127)	-0.033 (0.104)
User text 12	-0.404** (0.125)	0.216 (0.131)	0.087 (0.104)	-0.051 (0.095)	-0.240* (0.121)	-0.068 (0.126)	0.024 (0.101)
User text 13	-0.302* (0.129)	0.268* (0.132)	0.088 (0.107)	-0.068 (0.103)	0.097 (0.118)	-0.092 (0.128)	-0.094 (0.103)
User text 14	-0.155 (0.121)	0.084 (0.129)	0.097 (0.107)	-0.121 (0.096)	-0.205 (0.118)	0.003 (0.125)	0.041 (0.103)
User text 15	0.028 (0.124)	0.302* (0.128)	0.105 (0.105)	-0.039 (0.097)	0.011 (0.121)	0.108 (0.129)	0.023 (0.110)
User text 16	-0.261* (0.124)	0.187 (0.132)	-0.084 (0.110)	-0.096 (0.094)	-0.088 (0.116)	-0.185 (0.128)	-0.091 (0.107)
N observations	4,351	4,339	4,361	4,364	4,337	4,340	4,359
N respondents	2,223	2,219	2,229	2,230	2,216	2,215	2,227

* p < 0.05, ** p < 0.01, *** p < 0.001

Table N20: Complete regression results for Figure 6 in the main article (*citizen sample*)

	Prejudice	Push politician out of office	Opinion differences	Dislike politician's party	Dissatisfied with own life	Get a reaction from the politician	Get a reaction from other users
Woman politician	0.150*** (0.032)	0.069* (0.031)	-0.032 (0.028)	0.011 (0.028)	0.042 (0.030)	-0.039 (0.029)	0.009 (0.028)
Gendered text	0.149*** (0.031)	0.078* (0.030)	-0.010 (0.028)	0.019 (0.028)	0.070* (0.029)	0.020 (0.029)	0.033 (0.028)
Man user	0.152*** (0.031)	0.033 (0.030)	0.022 (0.027)	0.020 (0.028)	0.047 (0.029)	0.027 (0.029)	0.009 (0.028)
Co-partisan	0.101* (0.051)	0.053 (0.049)	0.043 (0.042)	0.080 (0.045)	0.112* (0.048)	0.099* (0.045)	0.055 (0.044)
Politician text 2	-0.133 (0.100)	-0.088 (0.097)	0.090 (0.088)	-0.024 (0.086)	-0.064 (0.098)	-0.137 (0.091)	-0.170 (0.088)
Politician text 3	-0.001 (0.102)	-0.077 (0.097)	0.099 (0.089)	0.009 (0.089)	0.189* (0.095)	0.117 (0.092)	0.119 (0.086)
Politician text 4	-0.050 (0.100)	-0.145 (0.096)	-0.025 (0.088)	-0.110 (0.088)	0.000 (0.094)	-0.052 (0.091)	-0.120 (0.088)
Politician text 5	-0.036 (0.102)	0.011 (0.097)	-0.099 (0.093)	-0.072 (0.090)	-0.032 (0.098)	-0.152 (0.096)	-0.070 (0.091)
Politician text 6	-0.213* (0.101)	-0.281** (0.097)	-0.070 (0.088)	-0.232** (0.090)	-0.002 (0.096)	-0.177* (0.090)	-0.117 (0.087)
Politician text 7	-0.151 (0.104)	-0.240* (0.100)	-0.209* (0.093)	-0.202* (0.092)	0.012 (0.097)	-0.116 (0.095)	-0.104 (0.090)
Politician text 8	0.086 (0.103)	-0.115 (0.098)	-0.091 (0.092)	0.034 (0.090)	0.144 (0.096)	0.024 (0.092)	0.035 (0.088)
Politician text 9	-0.041 (0.102)	-0.033 (0.095)	-0.076 (0.091)	-0.021 (0.087)	0.098 (0.095)	-0.220* (0.093)	-0.100 (0.087)
Politician text 10	-0.052 (0.100)	-0.085 (0.097)	-0.140 (0.093)	-0.089 (0.088)	0.034 (0.098)	-0.016 (0.093)	-0.150 (0.090)
Politician text 11	-0.291** (0.104)	-0.281** (0.096)	-0.046 (0.090)	-0.111 (0.088)	-0.108 (0.099)	-0.156 (0.092)	-0.178* (0.089)
Politician text 12	-0.108 (0.101)	-0.220* (0.095)	0.040 (0.088)	-0.101 (0.088)	-0.048 (0.096)	-0.191* (0.092)	-0.056 (0.087)
Politician text 13	-0.030 (0.099)	-0.149 (0.097)	-0.085 (0.091)	-0.155 (0.089)	0.006 (0.097)	-0.070 (0.093)	-0.107 (0.089)
Politician text 14	-0.131 (0.098)	-0.129 (0.096)	0.031 (0.087)	-0.069 (0.088)	-0.044 (0.095)	-0.075 (0.090)	-0.074 (0.087)
Politician text 15	-0.148 (0.101)	-0.205* (0.095)	-0.100 (0.090)	-0.202* (0.086)	-0.214* (0.096)	-0.150 (0.091)	-0.137 (0.088)
Politician text 16	0.025 (0.098)	-0.109 (0.094)	0.046 (0.088)	0.075 (0.086)	-0.058 (0.095)	-0.147 (0.092)	0.065 (0.085)
Politician text 17	-0.109 (0.099)	-0.234* (0.096)	-0.003 (0.090)	-0.069 (0.089)	-0.087 (0.096)	-0.144 (0.093)	-0.155 (0.090)
Politician text 18	0.082 (0.099)	-0.042 (0.096)	-0.042 (0.089)	-0.024 (0.087)	0.078 (0.094)	-0.099 (0.091)	0.056 (0.085)
Politician text 19	-0.110 (0.101)	-0.136 (0.098)	-0.023 (0.091)	-0.028 (0.087)	0.006 (0.097)	-0.027 (0.091)	-0.060 (0.091)
Politician text 20	-0.018 (0.100)	-0.081 (0.097)	0.053 (0.089)	-0.003 (0.087)	-0.041 (0.095)	-0.057 (0.090)	-0.038 (0.088)
User text 2	-0.162 (0.091)	-0.008 (0.086)	0.066 (0.078)	0.004 (0.080)	-0.083 (0.083)	-0.041 (0.083)	-0.064 (0.077)
User text 3	0.080 (0.089)	0.135 (0.085)	0.057 (0.079)	0.176* (0.080)	0.052 (0.085)	0.060 (0.083)	-0.010 (0.078)
User text 4	0.111 (0.088)	0.107 (0.084)	0.018 (0.079)	0.236** (0.079)	-0.012 (0.083)	0.053 (0.082)	-0.013 (0.076)
User text 5	-0.108 (0.090)	-0.068 (0.086)	-0.018 (0.078)	0.057 (0.080)	-0.031 (0.082)	-0.043 (0.083)	-0.045 (0.076)
User text 6	-0.128 (0.089)	0.052 (0.086)	-0.034 (0.079)	-0.018 (0.080)	-0.041 (0.083)	0.049 (0.081)	-0.145 (0.079)
User text 7	-0.154 (0.092)	-0.180* (0.088)	0.042 (0.080)	0.003 (0.080)	-0.131 (0.085)	0.038 (0.082)	-0.194* (0.079)
User text 8	-0.021 (0.090)	0.139 (0.087)	-0.039 (0.080)	0.016 (0.078)	0.008 (0.084)	0.003 (0.082)	-0.245** (0.080)
User text 9	-0.249** (0.090)	0.047 (0.086)	0.045 (0.080)	0.049 (0.081)	-0.208* (0.086)	-0.018 (0.084)	-0.082 (0.078)
User text 10	-0.148 (0.091)	-0.072 (0.088)	0.006 (0.080)	-0.028 (0.083)	0.026 (0.087)	-0.023 (0.084)	-0.139 (0.079)
User text 11	-0.163 (0.090)	0.056 (0.086)	0.088 (0.077)	0.107 (0.078)	0.051 (0.085)	0.004 (0.083)	-0.142 (0.078)
User text 12	-0.293** (0.090)	0.118 (0.085)	0.017 (0.078)	0.037 (0.079)	-0.194* (0.083)	-0.083 (0.083)	-0.203* (0.080)
User text 13	-0.228* (0.090)	0.206* (0.084)	0.020 (0.077)	0.016 (0.078)	-0.103 (0.083)	0.000 (0.082)	-0.151* (0.076)
User text 14	-0.118 (0.089)	0.014 (0.085)	0.038 (0.077)	0.112 (0.079)	0.012 (0.083)	0.068 (0.081)	0.031 (0.075)
User text 15	0.126 (0.089)	0.103 (0.087)	-0.010 (0.081)	0.141 (0.080)	0.133 (0.084)	0.105 (0.081)	-0.072 (0.077)
User text 16	-0.121 (0.091)	0.099 (0.088)	-0.233** (0.083)	-0.038 (0.082)	-0.192* (0.087)	-0.096 (0.086)	-0.186* (0.078)
N observations	10,618	10,604	10,625	10,632	10,610	10,609	10,619
N respondents	5,331	5,326	5,334	5,338	5,328	5,329	5,334

* p < 0.05, ** p < 0.01, *** p < 0.001

Table N21: Complete regression results for Figure 7 in the main article

	Politician	Citizen	Politician	Citizen
Woman politician × gendered text	0.333*** (0.094)	0.310*** (0.063)		
Woman politician × man user			0.323*** (0.095)	0.232*** (0.064)
Woman politician	0.086 (0.065)	-0.004 (0.044)	0.090 (0.066)	0.033 (0.045)
Gendered text	-0.022 (0.065)	-0.007 (0.044)		
Man user	0.076 (0.046)	0.150*** (0.031)	-0.085 (0.067)	0.035 (0.044)
Co-partisan	0.212*** (0.060)	0.104* (0.051)	0.207*** (0.059)	0.105* (0.051)
Politician text 2	0.001 (0.135)	-0.142 (0.099)	-0.010 (0.136)	-0.130 (0.100)
Politician text 3	-0.110 (0.140)	-0.006 (0.102)	-0.131 (0.141)	0.003 (0.102)
Politician text 4	-0.141 (0.140)	-0.048 (0.100)	-0.154 (0.140)	-0.046 (0.100)
Politician text 5	0.046 (0.144)	-0.043 (0.103)	0.030 (0.145)	-0.032 (0.102)
Politician text 6	-0.011 (0.148)	-0.213* (0.101)	-0.017 (0.148)	-0.210* (0.101)
Politician text 7	-0.186 (0.147)	-0.151 (0.104)	-0.204 (0.148)	-0.151 (0.103)
Politician text 8	-0.029 (0.141)	0.091 (0.103)	-0.055 (0.142)	0.089 (0.103)
Politician text 9	0.072 (0.139)	-0.039 (0.102)	0.050 (0.139)	-0.033 (0.102)
Politician text 10	0.033 (0.140)	-0.049 (0.100)	0.038 (0.141)	-0.056 (0.100)
Politician text 11	-0.258 (0.141)	-0.289** (0.104)	-0.255 (0.141)	-0.279** (0.103)
Politician text 12	-0.162 (0.140)	-0.108 (0.101)	-0.184 (0.140)	-0.106 (0.101)
Politician text 13	0.073 (0.142)	-0.028 (0.099)	0.079 (0.142)	-0.029 (0.098)
Politician text 14	0.096 (0.137)	-0.136 (0.098)	0.099 (0.138)	-0.133 (0.098)
Politician text 15	0.049 (0.135)	-0.150 (0.101)	0.050 (0.136)	-0.141 (0.101)
Politician text 16	0.134 (0.138)	0.027 (0.099)	0.143 (0.140)	0.030 (0.098)
Politician text 17	0.083 (0.140)	-0.112 (0.099)	0.060 (0.141)	-0.111 (0.099)
Politician text 18	0.175 (0.141)	0.081 (0.099)	0.166 (0.142)	0.083 (0.098)
Politician text 19	0.158 (0.137)	-0.111 (0.101)	0.142 (0.138)	-0.111 (0.101)
Politician text 20	-0.142 (0.134)	-0.022 (0.100)	-0.140 (0.135)	-0.021 (0.099)
User text 2	-0.309* (0.128)	-0.158 (0.091)	-0.326* (0.127)	-0.156 (0.091)
User text 3	-0.143 (0.122)	0.078 (0.089)	-0.132 (0.121)	0.090 (0.089)
User text 4	-0.119 (0.125)	0.121 (0.088)	-0.114 (0.125)	0.120 (0.088)
User text 5	-0.218 (0.125)	-0.103 (0.090)	-0.207 (0.125)	-0.099 (0.090)
User text 6	-0.422** (0.130)	-0.123 (0.088)	-0.417** (0.131)	-0.120 (0.089)
User text 7	-0.297* (0.129)	-0.154 (0.092)	-0.300* (0.129)	-0.151 (0.092)
User text 8	0.251* (0.122)	-0.022 (0.090)	0.247* (0.121)	-0.012 (0.090)
User text 9	-0.305* (0.125)	-0.245** (0.090)	-0.310* (0.124)	-0.243** (0.090)
User text 10	-0.350** (0.123)	-0.148 (0.091)	-0.345** (0.123)	-0.141 (0.091)
User text 11	-0.085 (0.128)	-0.158 (0.090)	-0.088 (0.129)	-0.157 (0.090)
User text 12	-0.395** (0.124)	-0.287** (0.090)	-0.392** (0.124)	-0.282** (0.091)
User text 13	-0.294* (0.129)	-0.222* (0.090)	-0.302* (0.129)	-0.223* (0.090)
User text 14	-0.143 (0.120)	-0.114 (0.089)	-0.147 (0.120)	-0.108 (0.089)
User text 15	0.037 (0.124)	0.128 (0.089)	0.041 (0.123)	0.137 (0.089)
User text 16	-0.261* (0.124)	-0.118 (0.091)	-0.252* (0.124)	-0.123 (0.091)
N observations	4,351	10,618	4,351	10,618
N respondents	2,223	5,331	2,223	5,331

* p < 0.05, ** p < 0.01, *** p < 0.001

References

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